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**Abstract**

This paper introduces a novel real GDP growth nowcasting strategy based on a distribution of nowcast values derived from a large dataset and multiple variable combinations, specifications and estimators. We exploit structured and unstructured data from The Bahamas, using eleven estimators from the econometrics and machine learning literature. The study begins describing our dataset with over three hundred variables from the national statistics system, satellite nighttime lights data for key geographic locations in the archipelago, and internet search trends. Next, we nowcast the seasonally-adjusted annualized quarter-on-quarter growth rate of real gross domestic product using multiple combinations of variables, specifications and estimators. Overall, the ensemble method produces a distribution of nowcasts that outperform a human-designed benchmark. This paper contributes a novel idea of exploiting a distribution of estimates rather than point-values from a determined specification or estimator.

Keywords: Nowcasting, Google Trends, Nighttime Lights, GDP growth, Time series, Machine Learning, Tourism, The Bahamas.

JEL Classification: C53, C55, E37, O47, C38, L83, O54.

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# 1 Introduction

Timely and reliable estimates of economic activity are essential for effective policymaking, particularly in small, open economies such as The Bahamas, subject to the volatility associated with natural disasters and external shocks, particularly those related to tourism activity. However, the availability of official gross domestic product (GDP) data, which by nature tends to be released a couple of months after the end of the quarter, often suffers from additional delays. For example, The Bahamas delayed the release of its 2024 GDP figures by at least eight months. This issue is widespread; globally, only 55 percent of countries publish quarterly GDP data in a timely manner, and just 72 percent do so for annual GDP figures (Akbal et al., 2023; Berry et al., 2018). This paper proposes a data-driven *nowcasting* framework to produce an accurate distribution of real or near real-time estimates of quarterly real GDP growth for The Bahamas, drawing on a broad set of structured and non-structured high-frequency data, and advanced time-series econometrics and machine learning techniques.

Nowcasting refers to the statistical procedure used to estimate the current or very near-term state of a variable using all available information (Hopp, 2024; Bok et al., 2018; Jansen et al., 2016; Kuzin et al., 2011; Marcellino and Schumacher, 2010; Giannone et al., 2008; Rünstler and Sédillot, 2003; Kitchen and Monaco, 2003). In contrast to forecasting, which projects the future realization of an outcome over the short or long term, nowcasting focuses on predicting the present or a very recent past period. Similar approaches have been applied to trade, poverty, inflation, and unemployment, among others (Chinn et al., 2023; Mahler et al., 2022; Larson and Sinclair, 2022; Lewis et al., 2022; Choi and Varian, 2012).

In this paper, we develop a comprehensive framework for nowcasting quarterly real GDP growth using a combination of traditional macroeconomic indicators and other non-traditional high-frequency data. The procedure begins with variable pre-selection through Least-Angle Regression (LARS) as in Chinn et al. (2023), identifying 28 variable groupings that outperform a benchmark; then, using these groupings, we evaluate different specifications (i.e. variants of the variable groupings) to try to address the main challenges found in the nowcasting and forecasting literature, namely: (i) mixed-frequencies, (ii) the dimensionality curse, (iii) ragged edges, (iv) macroeconomic dynamics (e.g., autocorrelation, persistence and lagged adjustment) and (v) omitted variable bias. To address the issue of dimensionality, we use Principal Component Analysis (PCA); to address mixed frequencies and ragged edges, we use vertical realignment (or "data flattening") and, to tackle macroeconomic dynamics and omitted variables bias, we include dependent variable lags. In addition to these data treatments, we use 11 estimators; among them: linear regression, regularization, decision trees, ensemble methods, and neural networks. Finally, given the real time or pseudo-real time environment of the nowcast exercise, that is, to account for different data availability at different moments of the nowcasting process, each specification is estimated at various time horizons or "vintages" (i.e., accounting for real-time data limitations (Dietterich, 2000)). This procedure results in over 1,800 nowcast estimates per time period (stemming from 28 groupings, 5 specifications and 11 estimators). We evaluate each of these nowcast estimates at every time horizon using their RMSE on the test set and retain only those performing better than the *median* estimate. Finally, we generate point-estimates by weighting them by their inverse RMSE, leveraging the strengths of diverse grouping-specification-estimator combinations, while also accounting for their uncertainty by obtaining a "distribution of nowcasts".

We test our approach on a dataset from a Small Island Developing State (SIDS) such as The Bahamas which, due to its archipelago nature and other SIDS features, is subject to multiple data constraints, not only in terms of consistency and availability of economy-wide data, but also in terms of significant publication delays and hard to maneuver data formats (e.g., PDF files rather than Excel or other easy-to-handle formats). While we compensate for high-frequency data scarcity by incorporating semi-structured real-time data such as Google Trends and remote-sensing Nighttime Lights (NTL), uncertainty coming from the inconsistency and availability of economy-wide data and significant publication lags is partially addressed by leveraging the *distribution of nowcasts*. These features make The Bahamian case well suited to test our proposed approach.

Overall, the results confirm that nowcast accuracy improves as more information becomes available, with model performance varying across publication vintages. The distribution of RMSE values shows that most model specifications outperform a human-designed benchmark, with median errors consistently below 0.80 percentage points. Filtering out poorly performing specifications further reduces average forecast errors to 0.72 percentage points, substantially lower than the 1.01 RMSE of the "human" benchmark. Out-of-sample nowcasts successfully capture the direction of GDP growth and approaches the magnitude by under 0.50 percentage points. Despite minor discrepancies in the final periods, estimates remain within tight confidence intervals, highlighting the robustness of the approach across information sets.

This paper has three contributions to the literature. First, the paper develops a data-driven variable selection procedure and proposes an ensemble nowcasting framework that combines multiple model specifications and estimation methods. Our strategy is a robust alternative to the standard practice of selecting a single preferred model (Hopp, 2024; Chinn et al., 2023), leveraging available information to its fullest. Second, the paper incorporates both structured and semi-structured real-time data sources, including high-frequency Google Trends and remote-sensing Nighttime Lights (NTL) data. Prior research suggests that satellite data may be especially valuable for small island economies, where key economic activity in the tourism sector occurs at night (Fontaine et al., 2025). In the context of the Bahamian archipelago, the use of NTL data is novel, capturing localized nighttime activity across a comprehensive list of hotels, ports, and airports –core sectors of the country's service-driven structure. Third, the paper introduces state-of-the-art machine learning and econometric methods for nowcasting economic activity in the Caribbean, an underrepresented region in the nowcasting literature. Previous studies have focused on nowcasting in Latin America (Arrieta-Prieto and Nieto, 2025; Bolivar, 2024; Tenorio and Perez, 2024; Galeano-Ramírez et al., 2021), perhaps with the exception of Suriname, a member of CARICOM (Bhaghoe and Ooft, 2023). Ours is the first comprehensive application to a Caribbean economy and offers practical support to policymakers and central bankers facing the challenges of external volatility, and the limitations of traditional data collection and dissemination methods.

The methods in this paper offer critical policy implications for small island economies like The Bahamas. By combining real-time indicators with flexible and scalable nowcasting models, policymakers can access timely estimates of economic activity before official GDP figures become available (Lewis et al., 2022). This is especially valuable in settings with large data publication lags and vulnerable to external volatility, such as shifts in tourism and foreign investment (Akbal et al., 2023). Integrating satellite imagery and Google Trends further provides near real time signals of economic activity that traditional surveys may overlook (Tenorio et al., 2025a,b; Larrahondo et al., 2024; Kohns and Bhattacharjee, 2023; Varian, 2014; Henderson et al., 2012; Choi and Varian, 2012). These tools also allow authorities to cross-validate official statistics, identifying potential errors, misreporting, or outdated assumptions in conventional indicators (Martinez, 2018), allowing the opportunity to improve national statistics. By improving the timeliness, accuracy, and breadth of near real-term economic monitoring, these methods strengthen the ability to face shocks, design agile policies, and allocate resources in a dynamic environment. Future extensions could study the development of sub-national and local estimates in countries with limitations for data collection, and nowcasting other key economic indicators suffering from delayed releases.

# 2 Literature Review

Nowcasting GDP –producing timely estimates of current output before its official release– has become a crucial tool for economic surveillance. Early methodologies were developed primarily for advanced economies, addressing key nowcasting challenges such as: (i) mixed-frequency data (see e.g., Kitchen and Monaco (2003); Mariano and Murasawa (2003); Baffigi et al. (2004); Ghysels et al. (2004, 2007); Clements and Galvão (2008); Kuzin et al. (2011)), (ii) staggered releases and the (iii) course of dimensionality (see e.g., Evans (2005); Giannone et al. (2006, 2008)). More recent approaches, include the use of Machine Learning (ML) and combinations of econometric and ML models (see, e.g., Marcellino and Schumacher (2010); Jansen et al. (2016); Grui and Lysenko (2017); Chakraborty and Joseph (2017); Makridakis et al. (2018); Richardson et al. (2018); Jardet and Meunier (2022); Chinn et al. (2023); Hopp (2024); Kant et al. (2025)). In emerging markets and developing economies, the task is even more complex due to sparser data availability and longer publication lags (Liu et al. (2011)). Consequently, a growing literature focuses on adapting nowcasting techniques to data-constrained environments, incorporating the use of non-structured data, and on evaluating whether combining multiple models can yield better performance than relying on a single method.

## 2.1 Nowcasting GDP in Emerging and Data-Scarce Economies

Researchers have applied nowcasting techniques in emerging markets by leveraging whatever high-frequency indicators are available and often incorporating statistical innovations to cope with limited data. One of the earliest emerging-economy applications is by Liu et al. (2011), who nowcast GDP growth for ten Latin American countries using a suite of models (AR, bridge equations, VAR, Bayesian VAR, and a factor model). Including monthly indicators was found to improve accuracy, and a dynamic factor model (DFM) provided the most accurate nowcasts overall across these countries. Similarly, Manuelito (2017) implemented a DFM for 17 Latin American and Caribbean economies, reporting that while an aggregate regional nowcast was fairly reliable, the accuracy at the individual country level depended heavily on the quality and timeliness of available data. These studies underscore that emerging-market GDP nowcasting can benefit from methods that efficiently use sparse data and extract common signals (as DFMs do).

Subsequent work has explored diverse approaches to enhance nowcasting in data-scarce settings. During the COVID-19 crisis, when traditional indicators became even more delayed or volatile, researchers turned to novel data sources and methods. For example, Sampi and Jooste (2020) used Google Mobility Index data within a MIDAS framework to nowcast monthly industrial production in Latin America, finding that mobility trends provided a reliable proxy for economic activity when official data were lagged. Saboin and Guerrero (2022) combined non-traditional indicators (such as satellite night-light intensity and Google search trends) with conventional economic series to nowcast GDP in five South American countries. Using a range of ten different econometric and machine learning models, they found that incorporating these unconventional, high-frequency data sources yielded nowcast improvements in cases where official economic data were especially limited, while providing smaller gains for countries with richer data. In a similar vein, Bolivar (2024) focused on Bolivia and demonstrated that a machine learning approach (integrating standard indicators with satellite imagery) can reduce the publication lag of official GDP estimates from six months to two, outperforming traditional time-series models and remaining robust even when the set of input features is varied.

Very recent studies in Latin America have conducted extensive comparisons of nowcasting methods. Flores et al. (2024) evaluates a dozen machine learning models (including regularized regressions and ensemble tree methods) against a benchmark DFM for nowcasting Peru's GDP using over 170 domestic and international indicators. The best-performing methods (e.g., LASSO, Ridge, and extreme gradient boosting) consistently outperform the DFM, and aggregating sector-level predictions (a "bottom-up" approach) further improves accuracy. Likewise, Tenorio and Perez (2024) incorporate both structured macroeconomic variables and unstructured text-based sentiment indicators in nowcasting quarterly GDP for Peru. They report that machine learning models (notably gradient boosting and regularized regressions) reduce nowcast errors by 20–25% compared to an AR(1) or DFM benchmark, with the gains particularly pronounced during periods of heightened uncertainty, when the inclusion of high-frequency news sentiment helps capture sudden changes.

Beyond Latin America, analogous efforts have been made in other regions. For instance, Barhoumi et al. (2022) address the severe data sparsity in Sub-Saharan African countries by employing a machine-learning framework to track economic activity in real time, enabling GDP growth assessments several quarters ahead of official statistics. In the Caribbean, Bhaghoe and Ooft (2023) apply multiple mixed-frequency approaches (factor-augmented MIDAS regressions, MF-VAR, and Bayesian MF-VAR) to nowcast Suriname's GDP in a data-constrained environment. They find that while different models perform adequately for short-term forecasts, combining the top-performing nowcasts into an ensemble yields a more robust prediction, mitigating individual model biases and variance. Collectively, these studies demonstrate how nowcasting techniques can be tailored to emerging economies by using creative data inputs and specialized models, and they highlight the continual improvement in accuracy as more (or more timely) information is incorporated.

## 2.2 Comparing and Combining Nowcasting Models

A key thread in the literature is whether using many models or an ensemble of forecasts can outperform a single best model. Many of the above studies implicitly address this by evaluating several modeling approaches. For example, the multi-country analysis of Liu et al. (2011) identified the DFM as superior among five methods, and recent country-specific works for Peru tested a wide array of machine learning algorithms to single out the most accurate predictors Flores et al. (2024); Tenorio and Perez (2024). The motivation for casting a wide net is that different models may excel under different conditions, and in data-limited contexts it is not obvious a priori which model will fare best.

An emerging consensus is that combining forecasts from multiple models often yields more robust nowcasts. In advanced-economy settings, Richardson et al. (2018) showed that averaging predictions from several machine learning algorithms improved GDP nowcast accuracy in New Zealand beyond any individual model's performance. In the Netherlands, Kant et al. (2025) found that simple forecast combinations (e.g., weighting models by inverse past error) achieved accuracy nearly on par with the single best method for nowcasting GDP. For emerging markets, explicit combination strategies have also proven beneficial. As noted, Bhaghoe and Ooft (2023) report that an ensemble of the best models improved short-horizon GDP predictions for Suriname. Even when an ensemble is not formally adopted, researchers often see value in model diversity: Barrios et al. (2021), for instance, compared six machine-learning techniques for Central American economies and observed that penalized regression models (which effectively shrink and select predictors) provided the most stable performance, though no single method decisively dominates in all situations.

Across the reviewed studies, a consistent pattern emerges: combining forecasts from multiple models generally improves robustness and accuracy compared to relying on a single specification. While some works (e.g., Liu et al. (2011)) identify a clear winner among tested models (DFM), others (Flores et al. (2024); Tenorio and Perez (2024)) show that ensembles or bottom-up aggregation outperform individual approaches. In data-scarce contexts, explicit combination strategies—such as those in Bhaghoe and Ooft (2023)—help mitigate model-specific biases and variance. Even in advanced economies (Richardson et al. (2018); Kant et al. (2025)), simple averaging or error-weighted combinations yield near-optimal results. Overall, the literature suggests that model diversity and forecast aggregation are particularly valuable under structural uncertainty and limited data availability. To the best of our knowledge, this study is the first attempt to use a comprehensive nowcasting approach for a Caribbean Basin economy: The Bahamas.

# 3 Data

The dependent variable is quarterly real GDP growth for the Bahamian economy from 2012 to 2023. The set of covariates is divided into two groups. The first includes traditional macroeconomic indicators, covering the real, fiscal, monetary, financial, and external sectors. The second group consists of semi-structured variables, including high-frequency indicators such as monthly Google Trends data and daily nighttime lights captured by the VIIRS satellite. We describe these variables in detail next.

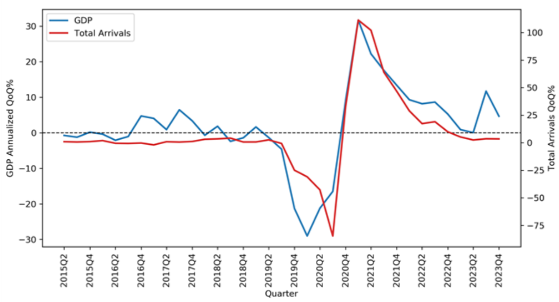
## 3.1 Structured data

Key GDP covariates are sourced from The Bahamas' Ministry of Finance (MoF), Ministry of Tourism (MoT), Central Bank (CBOB), and National Statistics Institute (BNSI). The dataset comprises 359 variables. Most macroeconomic indicators pertain to the real sector, including 140 variables on tourist arrivals disaggregated by mode of transport (air, sea, cruise, and total) and location, and 3 variables on construction activity (permits, starts, and completions). Energy and oil-related indicators account for 8 series, covering electricity generation, end-use electricity sales, oil imports, and Brent crude prices. Fiscal indicators comprise 29 series covering government revenue, expenditure, primary balance, and the overall fiscal surplus/deficit. The dataset also includes 25 international trade and external-sector variables, disaggregated by commodity and trading partner and including the current account balance, and 12 monetary, banking, and financial indicators encompassing money supply (M1, M2, M3), CPI, foreign reserves, loan rates, sectoral credit allocation (government, private, and other public-sector credit), banking-sector profitability and arrears, and the BISX equity index. Together with 141 unstructured high-frequency series (26 Google Trends keywords and 115 nighttime-lights aggregates) and the GDP target itself, this yields the full analytical dataset.[1] The relationships between GDP and several key leading indicators are illustrated in Figure 1. The series show strong co-movement, with tourist arrivals (Fig. 1a) and construction activity (Fig. 1b) exhibiting a very high correlation with eco-

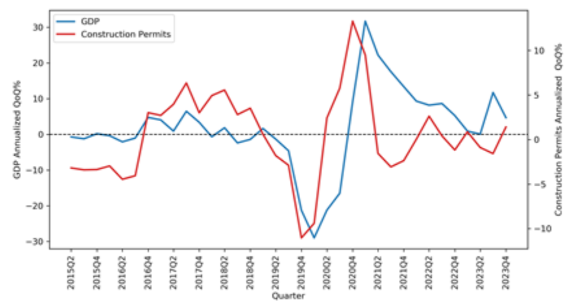
[1]Traditional macroeconomic indicators are described in Table 3.

nomic output, highlighting the dominance of tourism and related investment. The linkages with government revenue (Fig. 1c) and electricity generation (Fig. 1d) are also strong. Collectively, these consistent relationships across diverse sectors confirm that the selected structured data series are robust indicators of aggregate economic activity.

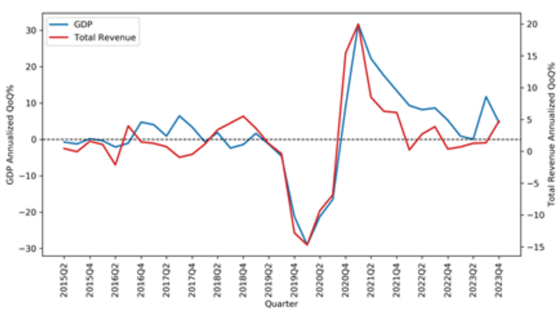
Figure 1: Structured data series and GDP (Annualized, QoQ%)




(a) GDP and total arrivals




(b) GDP and construction permits




(c) GDP and total government revenue


(d) GDP and electricity generated

**Source:** Own elaboration.

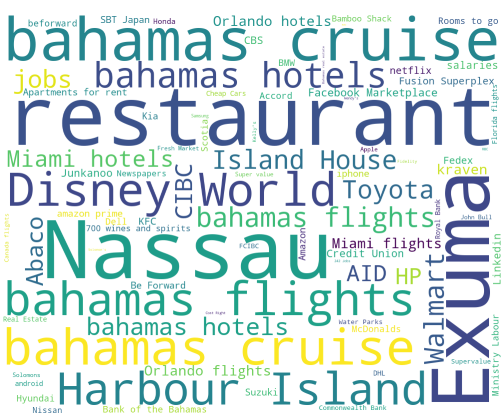
**Notes:** The panel above plots the quarterly growth rates (annualized, quarter-on-quarter percentage change) of GDP against four indicators: (a) total arrivals, (b) construction permits issued, (c) total government revenue, and (d) electricity generated. The data covers the period from 2016Q4 to 2024Q4. The purpose is to visualize the comovement between overall economic activity and these strucutred data indicators.

## 3.2 Unstructured data

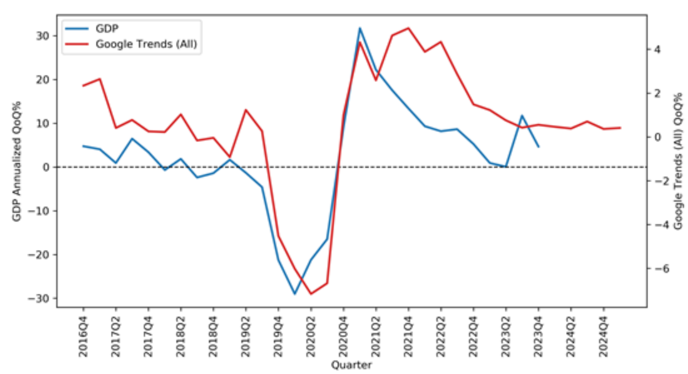
### 3.2.1 Google Trends

Google Trends provides an index of the relative search interest for specific keywords over time, capturing real-time signals of public attention and intent to consume or act. The data reflect the frequency with which users search for particular terms on Google, normalized to allow comparison across time and regions. This type of high-frequency, semi-structured data has become an increasingly valuable proxy for tracking economic activity, particularly in areas such as tourism, consumption, and mobility (Tenorio et al., 2025a,b; Larrahondo et al., 2024; Kohns and Bhattacharjee, 2023; Varian, 2014; Choi and Varian, 2012). To help identify relevant keywords for the Bahamian economy, although not representative of the Bahamian population, we conducted a small structured survey of local staff at the Inter-American Development Bank, asking respondents to list the most common online searches related to consumption, banking and finance, tourism services, property rentals, vehicle purchases, and other activities typically conducted via smartphones, navigation, or web platforms; the intention here was to identify key Google queries. Based on this input, we constructed a set of keyword series that reflect real-time interest in pursuing economic activity, displayed in Figure 2a by strength of correlation with our target variable (e.g., real GDP). We also include keywords related to foreigners' intent to travel by cruise, flight or book hotels in The Bahamas. The correlation with GDP is displayed in Figure 2b. These variables are added either as individual predictors or aggregated into a single index representing the average search interest across all selected keywords.

Figure 2: Google Trends and GDP




(a) Word cloud of Google Trends search words and GDP correlation




(b) Google Trends search index and GDP series (Annualized, QoQ%)

**Source:** Own elaboration.

**Notes:** This top panel displays the relationship between online search behavior and economic activity. Panel (a) visualizes selected keywords as a word cloud, where the size of each term corresponds to the strength of its correlation with GDP. Panel (b) tracks the quarterly (annualized, Quarter-on-Quarter percent change) movement of a composite index, the average of all search terms, against the official GDP series from 2016Q4 to 2024Q4.

### 3.2.2 Remote-sensing: satellite-based nighttime lights

We use daily satellite-based nighttime lights (NTL) data from the Visible Infrared Imaging Radiometer Suite (VIIRS), specifically the VNP46A2 product, which provides cloud-free radiance observations at high temporal and spatial resolution.[2] We extract daily NTL data from 2012 to the latest available date at specific point-locations of economic relevance across The Bahamas. This includes the coordinates of all 198 hotels listed on the official website of the Bahamian Ministry of Tourism, along with 7 major airports, 16 ports and shipyards, and 9 consumption centers encompassing shopping malls, clubs, water parks, public squares, and other key retail or leisure venues (illustrated in figure 3a). By capturing radiance at these precise locations, the NTL data offers a granular proxy for nighttime economic activity in tourism, transport, and consumption sectors—three pillars of the Bahamian economy. The analytical dataset includes NTL indicators constructed as the daily average and daily sum of radiance values across all locations within a given category (hotels, airports and ports, or consumption centers), as well as aggregate metrics computed as the mean or sum across all categories. Figure 3b plots the annualized quarter-on-quarter (QoQ) growth rates of both real GDP and the aggregate NTL radiance measure for all coordinates from 2016 to 2024. The co-movement of the two series, particularly during key economic swings, demonstrates a strong correlation and supports the use of high-frequency nighttime lights data for tracking economic activity.

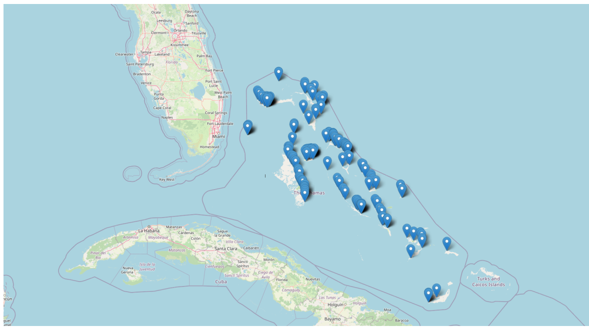
## 3.3 Data treatment

The analytical dataset is constructed using monthly frequency as the base. It consists of 359 correlates, spanning 160 months from January 2015 to June 2024. The series are seasonally adjusted using moving averages. Non-stationarity is mitigated by transforming all series into percent differences, allowing models to capture short-term fluctuations.

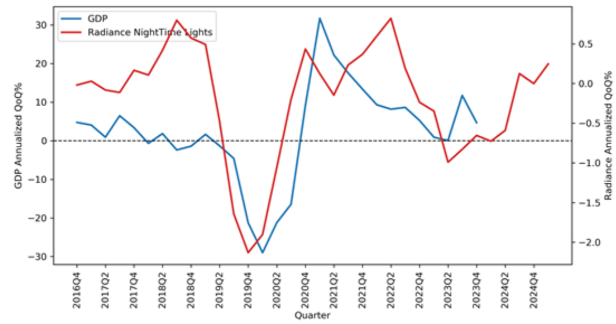
This dataset is divided into two samples: a training sample covering data up to May 2022, and a test sample spanning from the second quarter of 2022 to the second quarter of 2024 –the most recent data available for The Bahamas at the time of this study.

[2]The data was accessed through NASA's LAADS DAAC portal. NASA/NOAA Suomi NPP VIIRS Day/Night Band Nighttime Lights Daily L3 Global 500m VNP46A2. https://ladsweb.modaps.eosdis.nasa.gov/

Figure 3: Nighttime lights selected figures



(a) Map of coordinates used to measure nighttime lights radiance




(b) Nighttime radiance and GDP series (Annualized, QoQ%)

**Source:** Own elaboration.

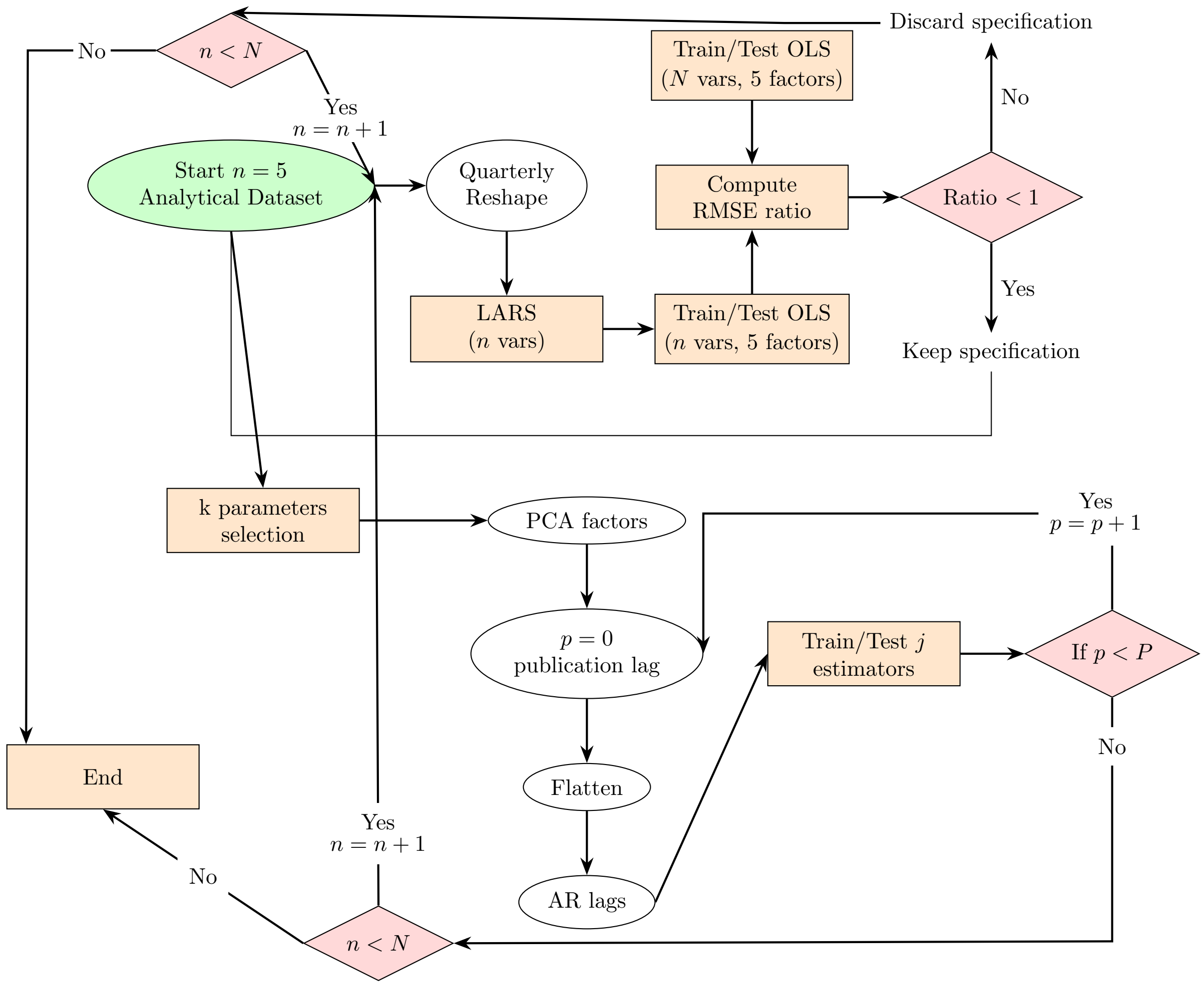
**Notes:** This figure presents selected visualizations from the analysis of NTL data as an economic indicator. Panel (a) shows a map of the specific coordinates (e.g., hotels, airports, consumption centers) selected for tracking NTL radiance. Panel (b) plots the quarterly growth rate of an aggregate NTL radiance measure against the official GDP growth rate (annualized, Quarter-on-Quarter percent change) from 2016Q4 to 2024Q4.

# 4 Methodology

This study implements a data-driven, iterative, multi-step procedure to nowcast real GDP growth. In the estimation algorithm, illustrated in Figure 4, the first step involves, following Chinn et al. (2023), the pre-selection of variables to be included in estimation by comparing the performance of Least Angle Regression (LARS) as in Bai and Ng (2008) over a maximum of $n$ variables against a benchmark. In the second step, a set of $k$ specifications is generated based on all $n$ variables selected and various data handling alternatives, such as: principal components (for dimensionality reduction), data flattening (for mixed-frequencies), and the inclusion of autoregressive lags (for macroeconomic dynamics and omitted variable bias). The third step iterates over these specifications, adjusting the analytical dataset according to the defined data handling parameters and across $p \leq P$ time horizons determined by the economic indicators release calendar. In the final step, we estimate $j$ econometric and machine learning estimators. The algorithm then repeats, pre-selecting $n+1$ variables over a range of $N$ maximum variables to be included in the nowcast. Overall, the algorithm results in the estimation of $k \times P \times j$ estimates for each variable group selected in the initial step.[3] Every step in the algorithm is detailed next.

[3]The actual estimation includes some specifications $i$ that cannot be estimated with model $m$ plus autoregressive models that have only one specification but $P$ information sets, such that the actual number is $k \times P \times j - \sum_{i=1}^{n} k_i m + P$.

Figure 4: Estimation algorithm




**Source:** Own elaboration.

**Notes:** The figure illustrates the estimation algorithm step-by-step, highlighting two feedback loops. The first step involves the pre-selection of variables to be included in estimation by comparing the performance of LARS regressions over a maximum of $n$ variables against a benchmark. In the second step, a set of $k$ specifications is generated based on all $n$ variables selected and various data handling alternatives, such as: principal components, data flattening, and autoregressive lags of the dependent variable. The third step iterates over these specifications, adjusting the analytical dataset according to the defined data handling parameters and across $p \leq P$ time horizons determined by the economic indicators release calendar. In the final step, we estimate $j$ econometric and machine learning estimators. The algorithm then repeats, pre-selecting $n + 1$ variables over a range of $N$ maximum variables to be included in the nowcast. Additionally, LARS estimation itself is implicitly iterative, progressively selecting $n$ variables with the largest correlation to the target variable by iterating over the full dataset. In the algorithm, data transformation is represented in ovals, decision nodes in rhombus, and computation in rectangles.

## 4.1 Pre-selection

The first step in the nowcasting procedure is variable pre-selection. As in Chinn et al. (2023), we employ LARS[4] (Bai and Ng, 2008), a technique suited for reducing high-dimensional data.[5] LARS initializes all coefficients at zero and incrementally builds a linear model by ranking the predictors most correlated with the current residuals, adjusting coefficients in a direction equiangular to the selected variables. However, because LARS does not accommodate mixed-frequency data, we first convert all variables to quarterly frequency.[6] Variables with more than three quarters of missing data are dropped. When there are missing values, these are imputed using the mean[7]. LARS selects variables until reaching a maximum number determined by the nowcaster. We iterate the LARS process across a range of sample sizes, from 5 to 100 variables, and compute the root mean squared error (RMSE) for each iteration. Consequently, model $n+1$ includes all variables from model $n$, plus one additional variable with the next highest correlation with residuals.

To decide whether to keep a combination of predictors, we first compute five principal components for the variables *selected* by LARS, and then we estimate an OLS regression using these principal components.[8] Subsequently, we compute the ratio of the RMSE to that of a benchmark OLS regression including the first five principal components from the *full* set of $N$ variables. Figure 5 displays each LARS combination of variables' RMSE ratios relative to the benchmark. Models with a ratio below the horizontal threshold line outperform the *full set* benchmark. We retain the variables selected by those models. This approach departs from Chinn et al. (2023) who, for simplicity, select 60 variables that generally correspond to the highest accuracy point for the LARS within all estimating horizons. In our application,

[4]LARS is selected because it outperforms other variable selection methods in the literature Chinn et al. (2023).

[5]High-dimensional data in nowcasting means working with large, complex datasets containing many variables, which presents both opportunities (more information) and challenges (collinearity, overfitting, variable selection).

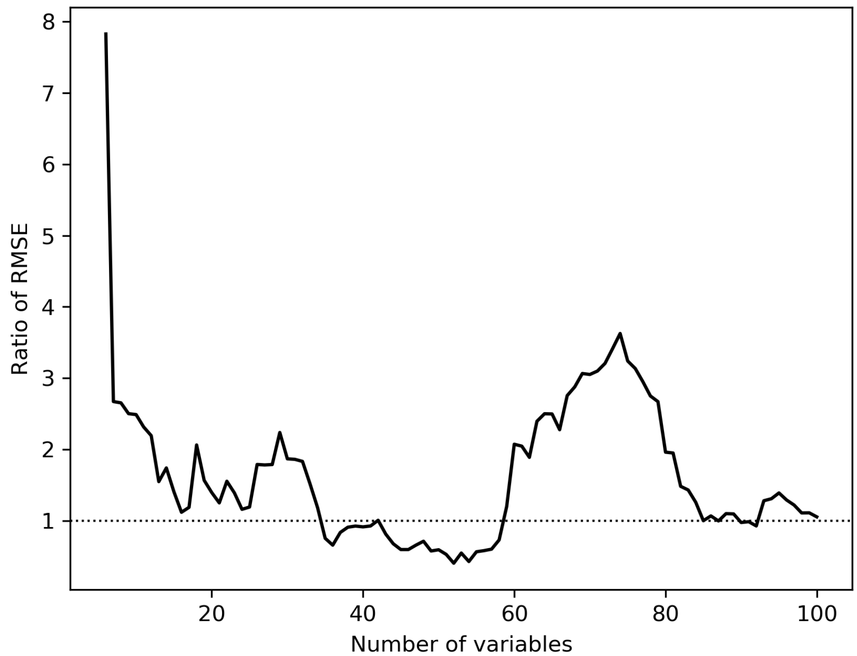
[6]The data aggregation to the quarterly frequency is used only in the variable selection process. Variables are aggregated using the mean, sum, or last value in the quarter, depending on the nature of the variable. Variable selection with LARS may be sensitive to the aggregation method selected. In our experience, we note that fewer specifications are below the threshold if the reshape algorithm uses only the quarterly mean. To clarify, this only occurs in this first step. When fitting the nowcasting models a flattening or stacking process is applied to the analytical monthly data.

[7]Other approaches (e.g., forward-filling, Kalman smoother, etc.) to address missing values have been used and discussed in the literature. Although we try different approaches for missing-value treatment, for the results presented here, we use the within-series mean, following Hopp (2024) who reports no significant differences when using other approaches)

[8]Chinn et al. (2023) tested LARS against three other methods: Sure Independence Screening (Fan and Lv (2008)), t-stat-based (Jurado et al. (2015)) and Iterated Bayesian Model Averaging (Martínez-Martín and Rusticelli (2021)).

we identify 28 model specifications that outperform the benchmark: all models with 35 to 58 variables, as well as those with 85, 87, and 90 to 92 variables. The largest of these specifications includes 92 variables.

Figure 5: Ratio of RMSE performance LARS to OLS.




**Source:** Own elaboration.

**Notes:** The figure plots the ratio of RMSE from each LARS variable combination first five principal components on a OLS regression relative to a benchmark OLS regression that includes the first five principal component from *all* variables in the analytical sample. The horizontal axis shows the maximum number of variables that LARS selects in each model. We transform the analytical sample to a quarterly frequency for both the LARS and benchmark models and impute missing values using the series mean.

## 4.2 Specifications

In the second step of the Nowcasting procedure, we evaluate several specification variants. We select them in three sub-steps considering different options or "parameters". First, we choose the number of principal components to include in the nowcast. Second, we address ragged edges by converting the monthly data into a quarterly matrix with additional vectors per variable at each period within the quarter. Third, we consider different autoregressive lags for the dependent variable. Rather than setting these parameters a priori, we estimate a wide range of model specifications, each reflecting the following combination of these three key parameters:

1. Factors: Principal Component Analysis (PCA) reduces the dimensionality of large datasets while preserving relevant information. By filtering out multicollinearity and noise, PCA generates synthetic factors that capture the co-variation among variables. These factors are expected to enhance model performance by summarizing the underlying structure of the data. However, because machine learning algorithms are designed to handle high-dimensional inputs directly, including PCA-derived factors may, in some cases, reduce performance. To account for this ambiguity, we estimate models with zero, three, and five factors.

2. Flattening: Ragged edges arise when real-time macroeconomic datasets contain variables released at different frequencies (e. g., monthly vs. quarterly) and with varying publication lags, resulting in an incomplete or jagged information set. In addition, some of the used estimators do not handle mixed-frequencies. To address these issues, we apply a vertical realignment or "flattening" procedure that transforms monthly variables into a consistent quarterly format while preserving variation from each month. This process reshapes the dataset into a wide format, with additional columns corresponding to every month in the quarter per each variable, including lags when information is not available for the quarter. Flattening allows constructing a rectangular data matrix suitable for model estimation while preserving the temporal ordering of information.[9] Since the optimal number of lags to include in the reshaping process is uncertain (e.g., in addition to the three values pertaining to the current quarter), we apply either three or five lags to the data.

3. Autoregressive (AR) lags: Including AR lags of GDP allows the nowcasting model to capture the persistence and temporal dynamics inherent in macroeconomic activity. GDP tends to follow a highly autocorrelated process, where past values provide useful information for predicting current and near-term outcomes. While traditional macroeconomic models deal with this issue, machine learning models require explicitly adding these lags. To assess the value of incorporating GDP's own history, we estimate models with zero and two autoregressive lags.

The nowcasting process in this study involves 197 models (i.e. variable groupings and specifications) per time horizon, organized as follows:

1. Baseline models: 28 initial specifications using three flattening lags in all models.

[9] By flattening the data, data dimensionality explodes even after applying variable selection because quarterly periods are added as one additional column for each variable. This may boost the effectiveness of PCA.

2. Expanded models: 28 additional specifications using four flattening lags for linear and regularized methods, and five lags for decision trees and the machine learning methods.
3. Models with three factors: 56 specifications that include three principal component factors –28 using the baseline models and 28 from the expanded group.
4. Models with five factors: 56 specifications that include five principal component factors in the baseline and expanded models.
5. Models with autoregressive lags: 28 specifications from the expanded models using five factors, and two autoregressive lags of GDP.
6. Human-selected model: A final specification based on expert judgment, using 17 selected variables, no factors or GDP lags, and four or five flattening lags across model types.

With this range of specifications we train and test different estimators from the econometrics and machine learning literature. These will be explained next.

## 4.3 Estimators

We group our nowcasting models into three broad classes: traditional econometric models, mixed-frequency and factor-based models, and machine learning approaches. This organization reflects how each class addresses the main challenges in real-time GDP estimation: the *curse of dimensionality*, which arises when the number of predictors exceeds the sample size; *ragged edges*, caused by asynchronous data releases and missing observations; and the need to capture *macroeconomic dynamics*, including lead–lag relationships and cross-variable interactions. Using multiple models is not only consistent with best practice in the literature (see Section 2), but also essential for robustness: different estimators excel under different conditions, and combining them often improves accuracy in data-constrained environments (Giannone et al., 2008; Bańbura et al., 2010; Bhaghoe and Ooft, 2023; Richardson et al., 2018).

Each class brings unique strengths: traditional models offer simplicity and interpretability; mixed-frequency and factor-based approaches address ragged edges and dimensionality while embedding macroeconomic structure; and machine learning models capture non-linearities and complex patterns. Given uncertainty about the true data-generating process and frequent structural changes in small open economies, relying on a single estimator is risky.

A multi-model strategy mitigates this risk, enables forecast combination, and produces a distribution of nowcasts rather than a single point estimate—an approach increasingly recommended in the literature (Bhaghoe and Ooft, 2023; Richardson et al., 2018). We will briefly mention the models while summarized formal explanations are in Appendix B.

### Traditional Econometric Models

Traditional models provide interpretable baselines and remain widely used in macroeconomic forecasting. Ordinary Least Squares (OLS) offers a simple benchmark, though its performance deteriorates under multicollinearity or when the predictor set is large (Wooldridge, 2010). To address these limitations, we include regularized regressions: LASSO (Tibshirani, 1996) imposes an L1 penalty to select a sparse subset of predictors, Ridge regression (Hoerl and Kennard, 1970) applies L2 shrinkage to stabilize estimates under collinearity, and Elastic Net (Zou and Hastie, 2005) combines both penalties for balanced variable selection and shrinkage. These methods partially mitigate the curse of dimensionality but do not natively handle ragged edges; missing data must be imputed or aligned before estimation. Their ability to capture macroeconomic dynamics is limited to the inclusion of lagged predictors, making them less flexible than multivariate or state-space approaches.

### Mixed-Frequency and Factor-Based Models

This class is designed to exploit asynchronous data releases and large indicator sets. Dynamic Factor Models (DFMs) summarize co-movements across many variables into a few latent factors, reducing dimensionality while preserving key business-cycle signals (Giannone et al., 2008). Cast in a state-space form, DFMs handle ragged edges through Kalman filtering and allow recursive updates as new data arrive. MIDAS regressions (Ghysels et al., 2004, 2016) incorporate monthly indicators into quarterly models using parsimonious lag polynomials, capturing lead–lag effects without overparameterization; ragged edges are addressed via truncation and weight re-normalization. Bayesian VARs (BVARs) extend traditional VARs by imposing shrinkage priors, enabling estimation of large systems and accommodating mixed-frequency data through latent-state representations (Bańbura et al., 2010; Schorfheide and Song, 2015). These models are particularly suited to emerging-market contexts, where data are incomplete and timeliness varies, and they capture macroeconomic dynamics more effectively than simple regressions by modeling factor evolution or full multivariate interactions.

### Machine Learning Models

Machine learning estimators complement econometric approaches by capturing non-linearities and complex interactions. Decision Trees partition the predictor space recursively, while Random Forests (Breiman, 2001) and Gradient Boosting Trees (Friedman, 2001) build tree ensembles that improve predictive accuracy and robustness. These models scale well to large predictor sets, partially alleviating dimensionality issues, but they require careful tuning to avoid overfitting. Ragged edges are not handled natively, so preprocessing (e.g., imputation or alignment) is necessary. Long Short-Term Memory (LSTM) networks (Hochreiter and Schmidhuber, 1997; Van Houdt et al., 2020) are designed for sequential data and excel at modeling long-range temporal dependencies, making them particularly attractive for capturing macroeconomic dynamics in noisy, high-frequency environments. While these models offer strong predictive performance, they come at the cost of interpretability and higher computational requirements.

Table 1: Estimator Classes and Key Features

| | Models | Curse of Dimensionality | Ragged Edges | Macroeconomic Dynamics | Strengths | Weaknesses | Comp. Cost | Key References |
|---|---|---|---|---|---|---|---|---|
| **Traditional econometric** | OLS; LASSO; Ridge; Elastic Net | OLS fragile in high-$p$. LASSO/Elastic Net perform selection. Ridge mitigates collinearity. | Not handled natively; requires alignment or imputation of missing releases. | OLS with engineered lags; limited cross-variable dynamics. | Simple, interpretable; fast baselines. | Limited flexibility; stationarity assumptions; no native handling of asynchronous releases. | Low | Enders (2008); Wooldridge (2010); Tibshirani (1996); Hoerl and Kennard (1970); Zou and Hastie (2005) |
| **Mixed-frequency / factor-based** | DFM; MIDAS; BVAR (mixed-frequency) | DFM reduces dimension via latent factors. BVAR employs Bayesian shrinkage. | State-space + Kalman filtering (DFM/BVAR). MIDAS uses truncation and weight renormalization. | Factors evolve as VARs; BVAR models multivariate lead–lag; MIDAS embeds distributed lags. | Handles large asynchronous panels; supports recursive real-time updates; strong macro structure. | Sensitivity to misspecification/structural breaks; MIDAS requires appropriate lag kernels. | Medium | Giannone et al. (2008); Ghysels et al. (2004, 2007); Bańbura et al. (2010); Schorfheide and Song (2015) |
| **Machine learning** | Decision Tree; Random Forest (RF); Gradient Boosting Trees (GBT); LSTM | Scales to many predictors (risk of overfitting if untuned). LSTM needs careful architecture/regularization. | Not handled natively; requires preprocessing (imputation, alignment) and data flattening. | Trees/GBT approximate dynamics via lagged features/interactions. LSTM learns long-range temporal dependencies. | Captures nonlinearities; strong predictive power; robust to complex interactions. | Lower interpretability; tuning sensitivity; data hunger (esp. deep learning). | High | Breiman et al. (1984); Breiman (2001); Friedman (2001); Hochreiter and Schmidhuber (1997); Van Houdt et al. (2020) |

**Source:** Own elaboration.

**Notes:** The table summarizes how estimator classes address three nowcasting challenges: *curse of dimensionality* (high predictor count), *ragged edges* (asynchronous releases), and *macroeconomic dynamics* (lead–lag and cross-variable interactions). Computational cost reflects typical implementation effort. Abbreviations: DFM = Dynamic Factor Model; MIDAS = Mixed Data Sampling; BVAR (MF) = mixed-frequency Bayesian VAR; RF = Random Forest; GBT = Gradient Boosting Trees; LSTM = Long Short-Term Memory.

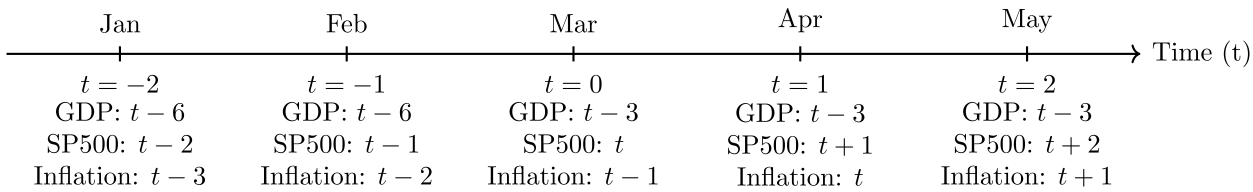
## 4.4 Training

Asynchronous publication dates pose a challenge in nowcasting because economic indicators are released at different times, often with significant delays relative to the current quarter, the aforementioned *ragged edge* problem. Figure 6 poses an illustration on how publication lags change data availability. For example, while stock market data is available in real time, GDP statistics are published weeks or even months after the reference period. Inflation, on the other hand, typically has a one-month lag as it is published one month after the period prices are measured. The result is an incomplete and unbalanced dataset at the time of prediction, where some variables are fully observed while others are missing or partially observed. These discrepancies create a "ragged edge" structure in the data. Nowcasting models must account for this mismatch to generate timely and accurate forecasts by combining imputation methods and database realignment.

As in Hopp (2024), we account for publication lags by training models across five different time horizons. These time horizons are based on a standard, representative release calendar of GDP figures in Latin America and The Caribbean.[10] First, we estimate each model (displayed above in section 4.3) using the information available two months before the end of the target quarter (e.g., January when forecasting first-quarter GDP). This corresponds to time $\Omega_{t-2}$, where any predictor (including GDP lags) is treated as missing if, according to its release calendar, it has not been released at that point. Missing values are replaced by imputing the mean of each variable. This information set is called a "vintage". In the second iteration, we use the vintage available one month before the end of the quarter $\Omega_{t-1}$. The third iteration uses the information available at the end of the quarter $\Omega_t$, when the GDP outcome is realized. We continue with two additional estimations $\Omega_{t+1}$ and $\Omega_{t+2}$, reflecting data releases one and two months after the quarter ends. The latter estimations do not include leading indicators from subsequent quarters but instead update the information set with indicators from the target quarter that were released after its end due to publication lags. In sum, we train the model on 5 *vintages*, one at each month of the nowcasting time span.

[10] In a representative Latin America and The Caribbean country, due to data collection and aggregation procedures, GDP figures are often released 2 months after the end of quarter. This implies that the GDP nowcasting exercise for a determined quarter begins the month the quarter starts (e.g. January if we are dealing with the first quarter) and ends two months after the last month of the quarter (e.g. May if we are dealing with the first quarter).

Figure 6: Publication Timeline Example




**Source:** Own elaboration.

**Notes:** This figure illustrates a timeline of data publication lags for the first quarter of a year and the following two months. In the first month of the quarter, GDP data is available only up to the second quarter of the previous year, while US stock market data is available in real time, and inflation figures are reported with a one-month delay. This pattern continues into February. By the end of the first quarter, GDP data for the third quarter of the previous year is released, and this update continues similarly through the next two months.

## 4.5 Testing

After training all models, we assess their performance using the RMSE over the test dataset. In total, the exercise produces 9,290 nowcast estimates for each GDP observation in the test set (197 model specifications across eleven estimators and five time horizons corresponding to data availability during the nowcasting cycle), yielding 1,858 estimates per vintage. This broad distribution includes both high-performing estimators and those inadequate for reliable GDP prediction due to their large RMSE. In the final step, we filter out models with poor performance by retaining only those whose RMSE falls below the median RMSE across the vintage.

## 4.6 Ensemble

After the algorithm finishes, the resulting distribution of specification-model nowcasts reveals widespread performance (measured by RMSE) across vintages. We look at each vintage since, in nowcasting, as new observations become available, estimates are expected to improve, leading to a decline in the RMSE (i.e. as more data gets published during the nowcasting period). We assess model accuracy in the test sample at each "artificial vintage", that is, we simulate the data as it would have been obtained at that specific point in time, given the typical publication lags of each variable.

When assessing performance by vintage, the distribution of performance metrics shows that, as we incorporate additional information, we notice that performance *worsens* in some specification-model combinations. We attribute this tendency to the performance of linear models which, in more recent vintages (and therefore where there is less mean imputation) the value of the RMSE increases exponentially (see Table 2 and Appendix Tables B2-B6). Moreover, this performance is particularly acute in specifications where there is no treatment to reduce dimensionality (e.g., baseline models without PCA).

To address these outliers, we take advantage of the large number of specification-model combinations by discarding those with a RMSE *above* the median at each vintage[11]. After this step, rather than selecting a single "best" specification, to account for both, data and model uncertainty, we preserve specification-model performance variance. In line with the nowcasting literature, we construct ensemble estimates by computing a weighted average of predictions. We do this by adding the inverse-RMSE- weighted nowcast of each specification-model combination.

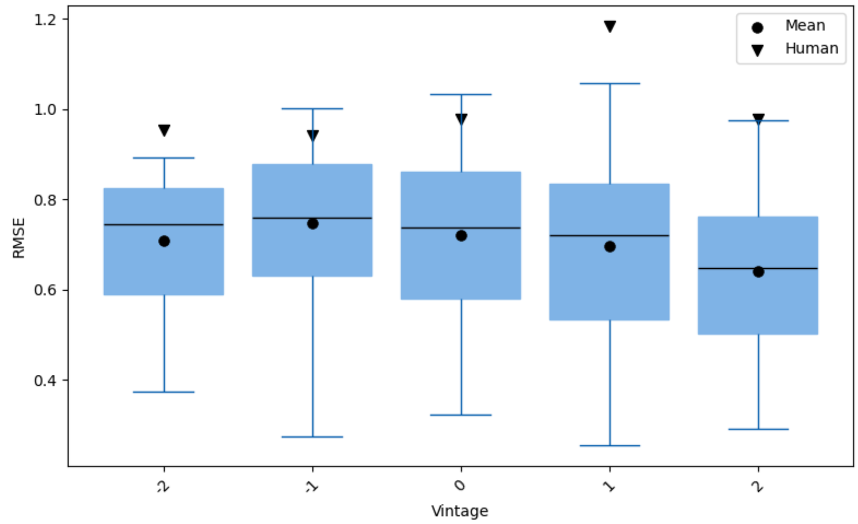
# 5 Results

## 5.1 Performance

The box-plot in Figure 7 shows RMSE distributions by vintage after correcting for outliers. As expected when nowcasting, the median error decreases as additional information becomes available. Moreover, most specification-model combinations outperform the human-designed benchmark. This result aligns with basic economic intuition: as models incorporate more information, their performance improves.

[11]The performance of each specification-model is assessed relative to the performance of others within the same vintage.

Figure 7: Distribution of RMSE across all specifications, publication lags, and estimators.




**Source:** Own elaboration.

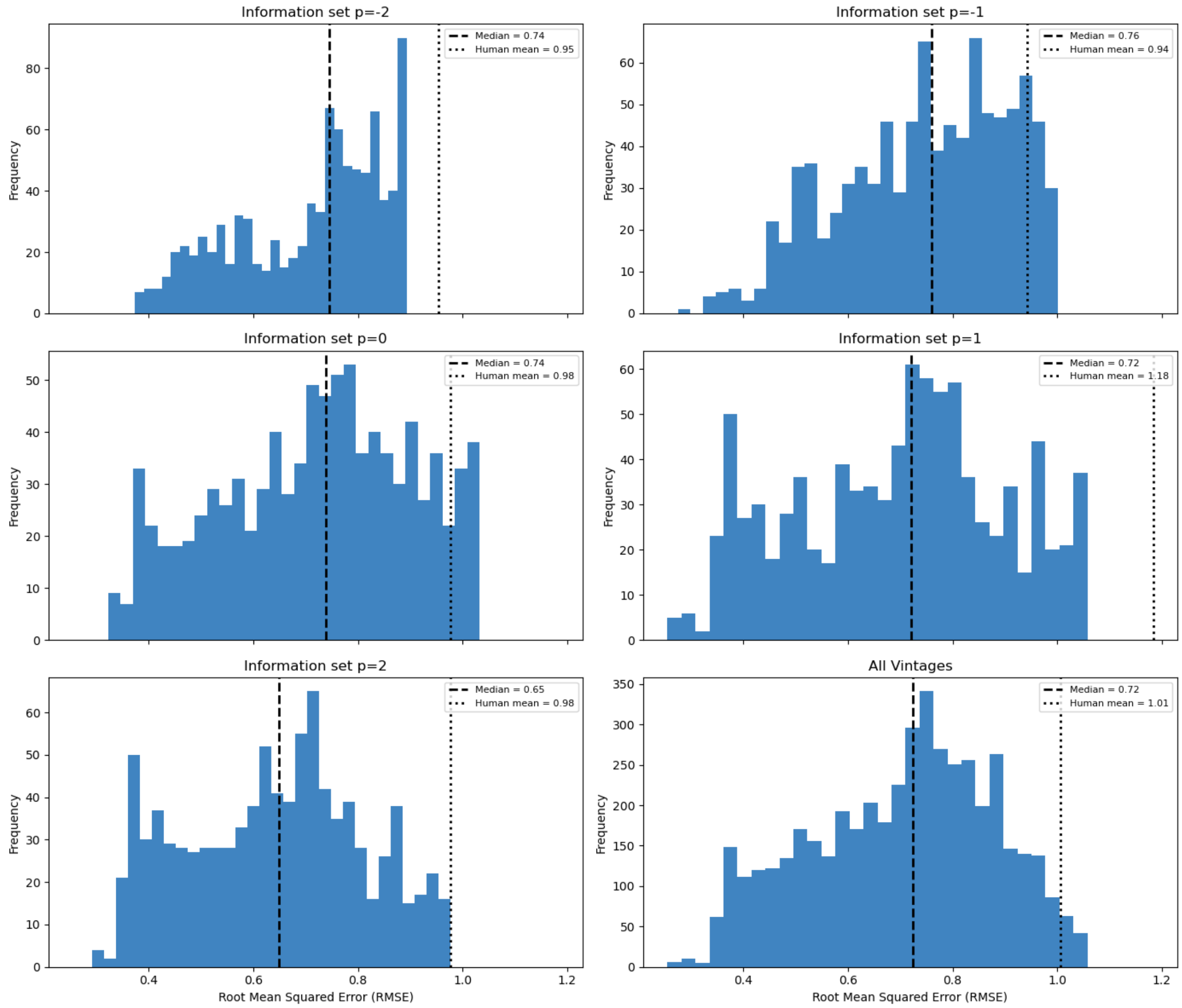
**Notes:** The figure displays the distribution of RMSE values for all specifications with RMSE below the median within each vintage (publication lag).

Figure 8 shows the distribution of RMSE at each vintage. The bottom-right chart shows that the average RMSE across all vintages is 0.72 percentage points. These estimates substantially outperform a benchmark specification developed using expert judgment ("human mean"[12] in the figure), which exhibits a RMSE of 1.01.[13]

[12]The term "mean" refers to the average across all 13 models.

[13]The human specification was developed without relying on pre-selection by LARS; instead, the human-expert benchmark specification (human1) for The Bahamas comprises 17 indicators based on expert judgment to span the principal channels of economic activity. The set includes fiscal aggregates (tax revenue, primary balance, current account), monetary and banking indicators (M3, private credit, loan rates, banking profits), real-sector activity proxies (construction permits, electricity generation, tourist arrivals), external and financial variables (total imports, exports to the United States, Brent crude price, Dow Jones Industrial Average, Bahamas Stock Exchange index), and two unstructured high-frequency series (a Google Trends keyword aggregate and a nighttime-lights radiance composite).

Figure 8: Distribution of RMSE across all specifications and estimators.




**Source:** Own elaboration.

**Notes:** The figure displays the distribution of RMSE values for all specifications with RMSE below the median within each vintage (publication lag).

We report the RMSE by specification and estimator in Table 2. The table presents RMSE values averaged across all vintages, with variable grouping-specifications defined in Section 4.2 listed in rows and estimators in columns.[14] Best-performing estimations are shaded in blue and worst-performing in red. RMSE values range from 0.40 to above 9 percentage points, with the upper end driven by linear estimators combined with baseline specifications

[14]See Tables 4–8 for averages by estimator within each vintage.

that do not address the curse of dimensionality. DFM and LSTM emerge as the most robust and accurate estimators across specification types, followed by BVAR and RF, while OLS, LASSO and ENET struggle in high-dimensional settings. This observed variation highlights that model accuracy depends not only on the chosen estimator but also on the specification and variable grouping, suggesting that relying on a single preferred model would omit useful information contained in alternative combinations.

Table 2: RMSE across specifications and models

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline*52 | | 0.64 | 1.33 | 2.30 | 1.08 | 2.30 | 0.78 | 0.75 | 3.52 | 3.52 | 0.74 |
| baseline*52p3 | 0.66 | 0.51 | 0.81 | 1.82 | 0.75 | 1.82 | 0.51 | 0.99 | 1.82 | 0.83 | 0.71 |
| baseline*52p5 | 0.65 | 0.42 | 0.78 | 1.65 | 0.84 | 1.65 | 0.46 | 0.95 | 1.65 | 0.90 | 0.79 |
| baseline*52p5l2 | | 0.40 | | | | | | 0.95 | | | |
| expanded35 | | | 1.54 | 7.77 | 1.30 | 8.12 | 0.74 | | 2.67 | 2.67 | 0.73 |
| expanded35p3 | | | 0.97 | 1.75 | 1.04 | 1.57 | 0.99 | | 1.75 | 1.46 | 0.89 |
| expanded35p5 | | | 0.94 | 2.44 | 0.98 | 3.28 | 0.71 | | 3.29 | 1.15 | 0.91 |
| expanded35p5l2 | | 0.50 | 0.93 | 2.44 | 1.00 | 3.28 | 0.68 | 1.21 | 3.29 | 1.15 | 0.91 |
| expanded36 | | | 1.55 | 7.30 | 1.32 | 7.49 | 0.75 | | 2.74 | 2.74 | 0.80 |
| expanded36p3 | | | 1.02 | 1.84 | 1.14 | 1.46 | 0.98 | | 1.84 | 1.59 | 1.01 |
| expanded36p5 | | | 0.89 | 3.29 | 1.13 | 3.57 | 0.57 | | 4.38 | 1.18 | 0.97 |
| expanded36p5l2 | | 0.49 | 0.89 | 3.29 | 1.13 | 3.57 | 0.58 | 1.19 | 4.38 | 1.18 | 0.97 |
| expanded37 | | | 1.54 | 7.30 | 1.32 | 7.49 | 0.75 | | 2.74 | 2.74 | 0.80 |
| expanded37p3 | | | 1.02 | 1.84 | 1.13 | 1.46 | 1.01 | | 1.84 | 1.59 | 1.01 |
| expanded37p5 | | | 0.90 | 3.29 | 1.13 | 3.57 | 0.57 | | 4.38 | 1.18 | 0.97 |
| expanded37p5l2 | | 0.50 | 0.90 | 3.29 | 1.14 | 3.57 | 0.59 | 1.13 | 4.38 | 1.18 | 0.97 |
| expanded38 | | | 1.54 | 7.30 | 1.32 | 7.49 | 0.78 | | 2.74 | 2.74 | 0.80 |
| expanded38p3 | | | 1.02 | 1.84 | 1.13 | 1.46 | 1.00 | | 1.84 | 1.59 | 1.01 |
| expanded38p5 | | | 0.89 | 3.29 | 1.14 | 3.57 | 0.56 | | 4.38 | 1.18 | 0.98 |
| expanded38p5l2 | | 0.53 | 0.89 | 3.29 | 1.14 | 3.57 | 0.58 | 1.20 | 4.38 | 1.18 | 0.97 |
| expanded39 | | | 1.55 | 7.30 | 1.33 | 7.49 | 0.74 | | 2.74 | 2.74 | 0.79 |
| expanded39p3 | | | 1.01 | 1.84 | 1.12 | 1.46 | 1.05 | | 1.84 | 1.59 | 1.01 |
| expanded39p5 | | | 0.89 | 3.29 | 1.11 | 3.57 | 0.54 | | 4.38 | 1.18 | 0.97 |
| expanded39p5l2 | | 0.85 | 0.89 | 3.29 | 1.13 | 3.57 | 0.61 | 1.06 | 4.38 | 1.18 | 0.96 |
| expanded40 | | | 1.53 | 6.70 | 1.34 | 6.92 | 0.75 | | 2.66 | 2.66 | 0.79 |
| expanded40p3 | | | 0.97 | 2.02 | 1.18 | 1.66 | 1.04 | | 2.02 | 1.77 | 1.02 |
| expanded40p5 | | | 0.97 | 3.32 | 1.26 | 3.68 | 0.89 | | 3.89 | 1.58 | 1.10 |
| expanded40p5l2 | | 0.68 | 0.97 | 3.32 | 1.25 | 3.68 | 0.86 | 1.04 | 3.89 | 1.58 | 1.09 |
| expanded41 | | | 1.52 | 6.30 | 1.33 | 6.77 | 0.84 | | 2.69 | 2.69 | 0.79 |
| expanded41p3 | | | 1.05 | 1.39 | 1.00 | 1.47 | 0.56 | | 1.39 | 0.99 | 0.80 |
| expanded41p5 | | | 0.82 | 2.27 | 0.98 | 2.32 | 0.59 | | 4.13 | 0.99 | 0.83 |
| expanded41p5l2 | | 0.43 | 0.80 | 2.27 | 0.98 | 2.32 | 0.59 | 0.98 | 4.13 | 0.99 | 0.82 |
| expanded43 | | | 1.38 | 4.77 | 1.29 | 4.95 | 0.75 | | 1.96 | 1.96 | 0.74 |
| expanded43p3 | | | 1.08 | 1.69 | 1.20 | 1.89 | 0.58 | | 1.69 | 0.90 | 0.79 |
| expanded43p5 | | | 1.00 | 2.05 | 1.33 | 2.91 | 0.50 | | 2.41 | 1.04 | 0.85 |
| expanded43p5l2 | | 0.41 | 0.99 | 2.05 | 1.32 | 2.91 | 0.50 | 1.02 | 2.41 | 1.04 | 0.84 |
| expanded44 | | | 1.38 | 4.46 | 1.27 | 4.67 | 0.73 | | 2.17 | 2.17 | 0.74 |
| expanded44p3 | | | 0.99 | 1.81 | 1.14 | 1.82 | 0.49 | | 1.81 | 0.78 | 0.73 |
| expanded44p5 | | | 1.18 | 2.14 | 1.19 | 1.87 | 0.41 | | 3.55 | 0.88 | 0.74 |
| expanded44p5l2 | | 0.41 | 1.14 | 2.14 | 1.21 | 1.87 | 0.43 | 1.01 | 3.55 | 0.88 | 0.75 |
| expanded45 | | | 1.34 | 3.88 | 1.26 | 3.98 | 0.75 | | 2.17 | 2.17 | 0.72 |
| expanded45p3 | | | 1.33 | 1.62 | 0.93 | 1.66 | 0.43 | | 1.62 | 0.69 | 0.84 |
| expanded45p5 | | | 1.01 | 2.26 | 1.04 | 2.13 | 0.43 | | 2.67 | 0.64 | 0.84 |
| expanded45p5l2 | | 0.43 | 1.01 | 2.26 | 1.04 | 2.13 | 0.43 | 1.10 | 2.67 | 0.64 | 0.84 |
| expanded46 | | | 1.36 | 3.85 | 1.26 | 3.96 | 0.72 | | 2.16 | 2.16 | 0.70 |
| expanded46p3 | | | 1.61 | 1.50 | 1.16 | 1.55 | 0.43 | | 1.50 | 0.67 | 0.93 |
| expanded46p5 | | | 1.29 | 2.39 | 1.27 | 2.31 | 0.44 | | 2.40 | 0.65 | 0.90 |
| expanded46p5l2 | | 0.44 | 1.28 | 2.39 | 1.28 | 2.31 | 0.45 | 1.02 | 2.40 | 0.65 | 0.91 |
| expanded47 | | | 1.69 | 3.97 | 1.21 | 4.29 | 0.80 | | 2.14 | 2.14 | 0.70 |
| expanded47p3 | | | 1.43 | 1.49 | 1.14 | 1.49 | 0.42 | | 1.49 | 0.65 | 0.92 |
| expanded47p5 | | | 1.28 | 2.32 | 1.26 | 1.77 | 0.41 | | 2.38 | 0.67 | 0.92 |
| expanded47p5l2 | | 0.44 | 1.23 | 2.32 | 1.25 | 1.77 | 0.42 | 1.01 | 2.38 | 0.67 | 0.92 |
| expanded48 | | | 1.71 | 3.28 | 1.19 | 3.63 | 0.86 | | 2.14 | 2.14 | 0.70 |
| expanded48p3 | | | 1.18 | 1.46 | 1.22 | 1.31 | 0.48 | | 1.46 | 0.68 | 0.97 |

Continued on next page

**Table 2 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| expanded48p5 | | | 1.13 | 1.96 | 1.29 | 1.62 | 0.43 | | 2.08 | 0.69 | 0.99 |
| expanded48p5l2 | | 0.44 | 1.13 | 1.96 | 1.30 | 1.62 | 0.43 | 1.01 | 2.08 | 0.69 | 1.00 |
| expanded49 | | | 1.50 | 3.02 | 1.23 | 3.37 | 0.73 | | 2.12 | 2.12 | 0.67 |
| expanded49p3 | | | 1.15 | 1.27 | 1.06 | 1.28 | 0.46 | | 1.27 | 0.74 | 0.92 |
| expanded49p5 | | | 1.24 | 1.85 | 1.15 | 1.41 | 0.42 | | 1.95 | 0.65 | 0.97 |
| expanded49p5l2 | | 0.45 | 1.24 | 1.85 | 1.18 | 1.41 | 0.43 | 1.00 | 1.95 | 0.65 | 0.97 |
| expanded50 | | | 1.57 | 2.62 | 1.22 | 2.93 | 0.73 | | 2.09 | 2.09 | 0.67 |
| expanded50p3 | | | 0.66 | 1.34 | 0.89 | 1.43 | 0.52 | | 1.34 | 0.72 | 0.78 |
| expanded50p5 | | | 0.80 | 1.40 | 1.03 | 1.01 | 0.51 | | 1.47 | 0.74 | 0.87 |
| expanded50p5l2 | | 0.42 | 0.80 | 1.40 | 1.03 | 1.01 | 0.47 | 1.04 | 1.47 | 0.74 | 0.86 |
| expanded51 | | | 1.49 | 2.85 | 1.21 | 3.35 | 0.75 | | 2.12 | 2.12 | 0.71 |
| expanded51p3 | | | 0.72 | 1.38 | 0.88 | 1.45 | 0.53 | | 1.38 | 0.74 | 0.77 |
| expanded51p5 | | | 0.93 | 1.61 | 0.97 | 1.22 | 0.47 | | 1.75 | 0.75 | 0.86 |
| expanded51p5l2 | | 0.83 | 0.93 | 1.61 | 0.99 | 1.22 | 0.47 | 1.05 | 1.75 | 0.75 | 0.86 |
| expanded52 | | | 1.44 | 2.19 | 1.00 | 2.62 | 0.75 | | 2.10 | 2.10 | 0.68 |
| expanded52p3 | | | 0.60 | 1.50 | 0.57 | 1.65 | 0.52 | | 1.50 | 0.72 | 0.58 |
| expanded52p5 | | | 0.66 | 1.61 | 0.70 | 0.97 | 0.48 | | 1.79 | 0.72 | 0.69 |
| expanded52p5l2 | | | 0.66 | 1.61 | 0.68 | 0.97 | 0.46 | | 1.79 | 0.72 | 0.69 |
| expanded53 | | | 1.43 | 2.33 | 0.98 | 2.70 | 0.79 | | 2.11 | 2.11 | 0.68 |
| expanded53p3 | | | 0.88 | 1.64 | 0.69 | 1.85 | 0.51 | | 1.64 | 1.26 | 0.69 |
| expanded53p5 | | | 0.66 | 1.58 | 0.84 | 1.12 | 0.48 | | 1.59 | 0.93 | 0.80 |
| expanded53p5l2 | | 0.41 | 0.66 | 1.58 | 0.85 | 1.12 | 0.52 | 0.96 | 1.59 | 0.93 | 0.80 |
| expanded54 | | | 0.91 | 2.43 | 0.60 | 2.87 | 0.74 | | 2.09 | 2.09 | 0.61 |
| expanded54p3 | | | 0.80 | 1.57 | 0.68 | 1.60 | 0.56 | | 1.58 | 1.17 | 0.67 |
| expanded54p5 | | | 0.88 | 1.43 | 0.75 | 0.91 | 0.51 | | 1.41 | 0.91 | 0.78 |
| expanded54p5l2 | | 0.85 | 0.87 | 1.43 | 0.72 | 0.91 | 0.48 | 0.84 | 1.41 | 0.91 | 0.76 |
| expanded55 | | | 1.02 | 2.76 | 0.60 | 3.07 | 0.72 | | 2.07 | 2.07 | 0.61 |
| expanded55p3 | | | 0.85 | 1.58 | 0.69 | 1.69 | 0.56 | | 1.58 | 0.75 | 0.70 |
| expanded55p5 | | | 0.80 | 1.68 | 0.69 | 1.38 | 0.57 | | 1.67 | 0.84 | 0.79 |
| expanded55p5l2 | | 0.86 | 0.80 | 1.68 | 0.70 | 1.38 | 0.57 | 0.84 | 1.67 | 0.84 | 0.79 |
| expanded56 | | | 0.98 | 2.84 | 0.59 | 3.12 | 0.69 | | 2.07 | 2.07 | 0.61 |
| expanded56p3 | | | 0.92 | 1.30 | 0.68 | 1.55 | 0.57 | | 1.30 | 0.69 | 0.66 |
| expanded56p5 | | | 0.94 | 1.68 | 0.55 | 0.97 | 0.59 | | 1.71 | 1.52 | 0.73 |
| expanded56p5l2 | | 0.40 | 0.94 | 1.68 | 0.54 | 0.97 | 0.61 | 0.83 | 1.71 | 1.52 | 0.73 |
| expanded57 | | | 0.94 | 2.84 | 0.58 | 3.12 | 0.82 | | 2.07 | 2.07 | 0.61 |
| expanded57p3 | | | 0.93 | 1.30 | 0.69 | 1.55 | 0.55 | | 1.30 | 0.69 | 0.66 |
| expanded57p5 | | | 0.94 | 1.68 | 0.55 | 0.97 | 0.60 | | 1.71 | 1.52 | 0.73 |
| expanded57p5l2 | | 0.41 | 0.94 | 1.68 | 0.55 | 0.97 | 0.61 | 0.83 | 1.71 | 1.52 | 0.73 |
| expanded58 | | | 1.03 | 2.84 | 0.59 | 3.12 | 0.82 | | 2.07 | 2.07 | 0.61 |
| expanded58p3 | | | 0.93 | 1.30 | 0.71 | 1.55 | 0.56 | | 1.30 | 0.69 | 0.66 |
| expanded58p5 | | | 0.94 | 1.68 | 0.54 | 0.97 | 0.58 | | 1.71 | 1.52 | 0.73 |
| expanded58p5l2 | | 0.78 | 0.94 | 1.68 | 0.55 | 0.97 | 0.59 | 0.83 | 1.71 | 1.52 | 0.73 |
| expanded85 | | | 1.07 | 2.06 | 0.57 | 2.04 | 0.71 | | 1.69 | 1.69 | 0.58 |
| expanded85p3 | | | 0.99 | 1.45 | 0.91 | 1.35 | 0.59 | | 1.53 | 0.83 | 0.84 |
| expanded85p5 | | | 0.88 | 0.88 | 0.82 | 0.79 | 0.58 | | 0.98 | 0.87 | 0.83 |
| expanded85p5l2 | | 0.45 | 0.88 | 0.88 | 0.83 | 0.79 | 0.52 | 0.87 | 0.98 | 0.87 | 0.83 |
| expanded87 | | | 1.15 | 1.08 | 0.55 | 1.09 | 0.76 | | 1.69 | 1.69 | 0.59 |
| expanded87p3 | | | 0.96 | 1.20 | 0.82 | 1.00 | 0.57 | | 1.27 | 0.90 | 0.83 |
| expanded87p5 | | | 1.01 | 0.92 | 0.80 | 0.93 | 0.56 | | 0.96 | 0.93 | 0.80 |
| expanded87p5l2 | | 0.44 | 1.01 | 0.92 | 0.81 | 0.93 | 0.58 | 0.86 | 0.96 | 0.93 | 0.80 |
| expanded90 | | | 1.18 | 1.27 | 0.55 | 1.26 | 0.73 | | 1.73 | 1.73 | 0.58 |
| expanded90p3 | | | 1.01 | 0.99 | 0.76 | 0.85 | 0.63 | | 1.00 | 0.85 | 0.85 |
| expanded90p5 | | | 0.97 | 0.87 | 0.69 | 0.98 | 0.57 | | 0.88 | 0.73 | 0.81 |
| expanded90p5l2 | | 0.66 | 0.97 | 0.87 | 0.70 | 0.98 | 0.57 | 0.86 | 0.88 | 0.73 | 0.81 |
| expanded91 | | | 1.11 | 1.36 | 0.53 | 1.35 | 0.79 | | 1.73 | 1.73 | 0.58 |
| expanded91p3 | | | 1.02 | 0.98 | 0.79 | 0.85 | 0.60 | | 1.00 | 0.85 | 0.86 |
| expanded91p5 | | | 1.04 | 0.94 | 0.79 | 0.93 | 0.62 | | 0.95 | 0.63 | 0.83 |
| expanded91p5l2 | | 0.69 | 1.04 | 0.94 | 0.80 | 0.93 | 0.61 | 0.86 | 0.95 | 0.63 | 0.83 |
| expanded92 | | | 1.11 | 1.38 | 0.52 | 1.37 | 0.75 | | 1.72 | 1.72 | 0.57 |
| expanded92p3 | | | 1.08 | 0.92 | 0.77 | 0.89 | 0.56 | | 0.93 | 0.85 | 0.83 |
| expanded92p5 | | | 1.03 | 0.99 | 0.77 | 0.97 | 0.57 | | 1.01 | 0.63 | 0.81 |
| expanded92p5l2 | | 0.63 | 1.03 | 0.99 | 0.77 | 0.97 | 0.57 | 0.83 | 1.01 | 0.63 | 0.81 |
| human1 | 0.59 | 0.71 | 1.08 | 1.73 | 0.80 | 1.77 | 0.54 | | 1.03 | 1.08 | 0.73 |
| baseline35 | | 0.43 | 1.56 | 9.59 | 1.38 | 9.59 | 0.71 | 0.80 | 6.19 | 6.19 | 0.86 |
| baseline35p3 | 1.26 | 0.52 | 1.07 | 2.14 | 1.30 | 2.14 | 1.00 | 1.33 | 2.14 | 1.58 | 1.07 |
| baseline35p5 | 0.78 | 0.51 | 1.03 | 2.07 | 1.21 | 2.07 | 0.67 | 1.21 | 2.38 | 1.38 | 1.06 |
| baseline36 | | 0.43 | 1.55 | 9.36 | 1.40 | 9.36 | 0.69 | 0.79 | 5.99 | 5.99 | 0.90 |
| baseline36p3 | 1.30 | 0.51 | 1.05 | 2.22 | 1.32 | 2.22 | 0.99 | 1.35 | 2.22 | 1.64 | 1.16 |
| baseline36p5 | 0.81 | 0.57 | 1.08 | 2.24 | 1.34 | 2.24 | 0.57 | 1.19 | 2.26 | 1.45 | 1.12 |
| baseline37 | | 0.43 | 1.56 | 9.36 | 1.41 | 9.36 | 0.77 | 0.77 | 5.99 | 5.99 | 0.90 |

Continued on next page

**Table 2 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline37p3 | 1.31 | 0.50 | 1.05 | 2.22 | 1.31 | 2.22 | 1.01 | 1.36 | 2.22 | 1.64 | 1.16 |
| baseline37p5 | 0.84 | 0.50 | 1.09 | 2.24 | 1.31 | 2.24 | 0.58 | 1.13 | 2.26 | 1.45 | 1.12 |
| baseline38 | | 0.43 | 1.56 | 9.36 | 1.41 | 9.36 | 0.73 | 0.80 | 5.99 | 5.99 | 0.92 |
| baseline38p3 | 1.24 | 0.43 | 1.04 | 2.22 | 1.31 | 2.22 | 1.00 | 1.37 | 2.22 | 1.64 | 1.16 |
| baseline38p5 | 0.80 | 0.49 | 1.09 | 2.24 | 1.31 | 2.24 | 0.58 | 1.20 | 2.26 | 1.45 | 1.13 |
| baseline39 | | 0.43 | 1.56 | 9.36 | 1.41 | 9.36 | 0.72 | 0.74 | 5.99 | 5.99 | 0.91 |
| baseline39p3 | 1.19 | 0.43 | 1.05 | 2.22 | 1.32 | 2.22 | 0.99 | 1.15 | 2.22 | 1.64 | 1.16 |
| baseline39p5 | 0.77 | 0.46 | 1.08 | 2.24 | 1.32 | 2.24 | 0.58 | 1.06 | 2.26 | 1.45 | 1.12 |
| baseline40 | | 0.78 | 1.54 | 9.00 | 1.41 | 9.00 | 0.69 | 0.72 | 6.11 | 6.11 | 0.91 |
| baseline40p3 | 1.22 | 0.43 | 1.31 | 2.25 | 1.41 | 2.25 | 1.05 | 1.15 | 2.25 | 1.69 | 1.17 |
| baseline40p5 | 0.78 | 0.47 | 1.31 | 3.30 | 1.44 | 3.30 | 0.85 | 1.04 | 3.35 | 1.87 | 1.18 |
| baseline41 | | 0.79 | 1.57 | 8.93 | 1.41 | 8.93 | 0.81 | 0.72 | 6.09 | 6.08 | 0.90 |
| baseline41p3 | 0.68 | 0.59 | 1.19 | 1.86 | 1.22 | 1.86 | 0.55 | 1.07 | 1.86 | 1.22 | 0.93 |
| baseline41p5 | 0.75 | 0.43 | 0.98 | 2.56 | 1.17 | 2.56 | 0.58 | 0.98 | 2.55 | 1.27 | 0.91 |
| baseline43 | | 0.78 | 1.37 | 6.13 | 1.38 | 6.13 | 0.78 | 0.78 | 3.37 | 3.37 | 0.87 |
| baseline43p3 | 0.92 | 0.50 | 1.30 | 2.40 | 1.36 | 2.40 | 0.59 | 1.07 | 2.40 | 1.12 | 0.93 |
| baseline43p5 | 0.90 | 0.41 | 1.17 | 2.64 | 1.35 | 2.64 | 0.51 | 1.02 | 2.64 | 1.12 | 0.94 |
| baseline44 | | 0.74 | 1.35 | 5.61 | 1.32 | 5.61 | 0.77 | 0.78 | 3.67 | 3.67 | 0.86 |
| baseline44p3 | 0.90 | 0.49 | 1.12 | 2.49 | 1.30 | 2.49 | 0.48 | 1.06 | 2.49 | 1.03 | 0.88 |
| baseline44p5 | 0.90 | 0.41 | 1.00 | 2.18 | 1.26 | 2.18 | 0.47 | 1.01 | 2.19 | 0.96 | 0.86 |
| baseline45 | | 0.78 | 1.23 | 4.88 | 1.32 | 4.88 | 0.80 | 0.81 | 3.66 | 3.66 | 0.81 |
| baseline45p3 | 0.90 | 0.47 | 1.20 | 2.03 | 1.20 | 2.03 | 0.44 | 1.18 | 2.03 | 0.95 | 0.94 |
| baseline45p5 | 0.85 | 0.44 | 1.23 | 2.65 | 1.29 | 2.65 | 0.43 | 1.10 | 2.66 | 0.96 | 0.94 |
| baseline46 | | 0.77 | 1.23 | 4.82 | 1.32 | 4.82 | 0.78 | 0.76 | 3.66 | 3.66 | 0.79 |
| baseline46p3 | 0.94 | 0.54 | 1.39 | 1.62 | 1.25 | 1.62 | 0.44 | 1.07 | 1.62 | 0.88 | 0.98 |
| baseline46p5 | 0.85 | 0.43 | 1.39 | 2.56 | 1.31 | 2.56 | 0.41 | 1.02 | 2.57 | 0.95 | 0.99 |
| baseline47 | | 0.77 | 1.44 | 4.92 | 1.28 | 4.92 | 0.81 | 0.75 | 3.64 | 3.63 | 0.77 |
| baseline47p3 | 0.95 | 0.49 | 1.39 | 1.70 | 1.24 | 1.70 | 0.41 | 1.06 | 1.70 | 0.83 | 0.97 |
| baseline47p5 | 0.87 | 0.44 | 1.40 | 2.70 | 1.28 | 2.70 | 0.40 | 1.01 | 2.71 | 0.89 | 0.97 |
| baseline48 | | 0.73 | 1.45 | 3.63 | 1.27 | 3.63 | 0.77 | 0.76 | 3.64 | 3.64 | 0.76 |
| baseline48p3 | 0.89 | 0.49 | 1.36 | 1.78 | 1.26 | 1.78 | 0.47 | 1.09 | 1.78 | 0.82 | 1.00 |
| baseline48p5 | 0.87 | 0.44 | 1.30 | 2.39 | 1.28 | 2.39 | 0.43 | 1.01 | 2.42 | 0.89 | 1.02 |
| baseline49 | | 0.76 | 1.37 | 3.44 | 1.27 | 3.44 | 0.81 | 0.76 | 3.59 | 3.59 | 0.75 |
| baseline49p3 | 0.85 | 0.48 | 1.29 | 1.77 | 1.15 | 1.77 | 0.47 | 1.08 | 1.77 | 0.79 | 0.97 |
| baseline49p5 | 0.76 | 0.46 | 1.35 | 2.38 | 1.15 | 2.38 | 0.40 | 1.00 | 2.41 | 0.85 | 0.98 |
| baseline50 | | 0.75 | 1.31 | 2.97 | 1.26 | 2.98 | 0.75 | 0.79 | 3.54 | 3.54 | 0.75 |
| baseline50p3 | 0.71 | 0.70 | 1.05 | 1.90 | 0.96 | 1.90 | 0.55 | 1.10 | 1.90 | 0.84 | 0.90 |
| baseline50p5 | 0.72 | 0.45 | 1.09 | 2.19 | 1.11 | 2.19 | 0.47 | 1.04 | 2.21 | 1.01 | 0.95 |
| baseline51 | | 0.72 | 1.29 | 3.14 | 1.27 | 3.14 | 0.68 | 0.80 | 3.58 | 3.58 | 0.77 |
| baseline51p3 | 0.70 | 0.50 | 1.09 | 1.88 | 0.88 | 1.88 | 0.49 | 1.12 | 1.88 | 0.85 | 0.89 |
| baseline51p5 | 0.70 | 0.45 | 1.12 | 2.13 | 1.06 | 2.13 | 0.47 | 1.05 | 2.14 | 1.01 | 0.93 |
| baseline53 | | 0.67 | 1.30 | 2.48 | 1.06 | 2.60 | 0.77 | 0.77 | 3.53 | 3.53 | 0.74 |
| baseline53p3 | 0.70 | 0.51 | 0.96 | 1.93 | 0.78 | 1.93 | 0.50 | 0.99 | 1.93 | 0.87 | 0.75 |
| baseline53p5 | 0.63 | 0.42 | 1.06 | 2.23 | 0.87 | 2.23 | 0.49 | 0.96 | 2.24 | 1.14 | 0.81 |
| baseline54 | | 0.63 | 1.03 | 2.60 | 0.58 | 2.72 | 0.75 | 0.71 | 3.50 | 3.50 | 0.65 |
| baseline54p3 | 0.65 | 0.49 | 1.01 | 1.61 | 0.86 | 1.61 | 0.56 | 0.87 | 1.61 | 0.80 | 0.77 |
| baseline54p5 | 0.65 | 0.41 | 1.07 | 2.26 | 0.93 | 2.26 | 0.47 | 0.84 | 2.27 | 1.10 | 0.84 |
| baseline55 | | 0.64 | 1.20 | 2.99 | 0.58 | 3.11 | 0.75 | 0.71 | 3.49 | 3.49 | 0.65 |
| baseline55p3 | 0.66 | 0.49 | 1.04 | 1.79 | 0.84 | 1.79 | 0.57 | 0.87 | 1.79 | 0.81 | 0.77 |
| baseline55p5 | 0.64 | 0.81 | 1.11 | 2.21 | 0.87 | 2.21 | 0.57 | 0.84 | 2.22 | 0.97 | 0.82 |
| baseline56 | | 0.60 | 1.19 | 3.07 | 0.57 | 3.19 | 0.75 | 0.71 | 3.49 | 3.49 | 0.65 |
| baseline56p3 | 0.63 | 0.50 | 1.17 | 1.47 | 0.80 | 1.47 | 0.57 | 0.85 | 1.47 | 0.81 | 0.70 |
| baseline56p5 | 0.63 | 0.43 | 1.01 | 2.05 | 0.79 | 2.05 | 0.60 | 0.83 | 2.06 | 1.01 | 0.74 |
| baseline57 | | 0.60 | 1.12 | 3.07 | 0.58 | 3.19 | 0.80 | 0.71 | 3.49 | 3.49 | 0.64 |
| baseline57p3 | 0.65 | 0.50 | 1.17 | 1.47 | 0.80 | 1.47 | 0.56 | 0.85 | 1.47 | 0.81 | 0.70 |
| baseline57p5 | 0.64 | 0.43 | 1.01 | 2.05 | 0.79 | 2.05 | 0.58 | 0.83 | 2.06 | 1.01 | 0.74 |
| baseline58 | | 0.60 | 1.07 | 3.07 | 0.57 | 3.19 | 0.76 | 0.71 | 3.49 | 3.49 | 0.65 |
| baseline58p3 | 0.66 | 0.50 | 1.17 | 1.47 | 0.80 | 1.47 | 0.55 | 0.85 | 1.47 | 0.81 | 0.70 |
| baseline58p5 | 0.64 | 0.43 | 1.01 | 2.05 | 0.78 | 2.05 | 0.63 | 0.83 | 2.06 | 1.01 | 0.74 |
| baseline85 | | 0.40 | 1.21 | 2.08 | 0.55 | 2.09 | 0.69 | 0.74 | 2.74 | 2.74 | 0.61 |
| baseline85p3 | 0.58 | 0.43 | 0.98 | 1.14 | 0.67 | 1.14 | 0.62 | 0.89 | 1.14 | 0.82 | 0.79 |
| baseline85p5 | 0.62 | 0.45 | 0.85 | 1.16 | 0.71 | 1.16 | 0.53 | 0.87 | 1.16 | 1.13 | 0.83 |
| baseline87 | | 0.41 | 1.24 | 1.10 | 0.53 | 1.10 | 0.75 | 0.73 | 2.74 | 2.74 | 0.61 |
| baseline87p3 | 0.57 | 0.43 | 0.94 | 1.09 | 0.66 | 1.09 | 0.59 | 0.87 | 1.09 | 0.82 | 0.76 |
| baseline87p5 | 0.63 | 0.44 | 0.93 | 1.24 | 0.76 | 1.24 | 0.60 | 0.86 | 1.24 | 0.92 | 0.80 |
| baseline90 | | 0.46 | 1.20 | 1.29 | 0.54 | 1.27 | 0.78 | 0.72 | 2.75 | 2.75 | 0.61 |
| baseline90p3 | 0.56 | 0.42 | 0.84 | 1.05 | 0.65 | 1.05 | 0.61 | 0.87 | 1.05 | 0.83 | 0.77 |
| baseline90p5 | 0.61 | 0.68 | 0.90 | 1.06 | 0.69 | 1.06 | 0.59 | 0.86 | 1.06 | 0.86 | 0.79 |
| baseline91 | | 0.41 | 1.31 | 1.37 | 0.54 | 1.35 | 0.75 | 0.72 | 2.74 | 2.73 | 0.61 |
| baseline91p3 | 0.57 | 0.42 | 0.84 | 1.06 | 0.69 | 1.06 | 0.60 | 0.88 | 1.06 | 0.83 | 0.79 |

Continued on next page

**Table 2 – continued**

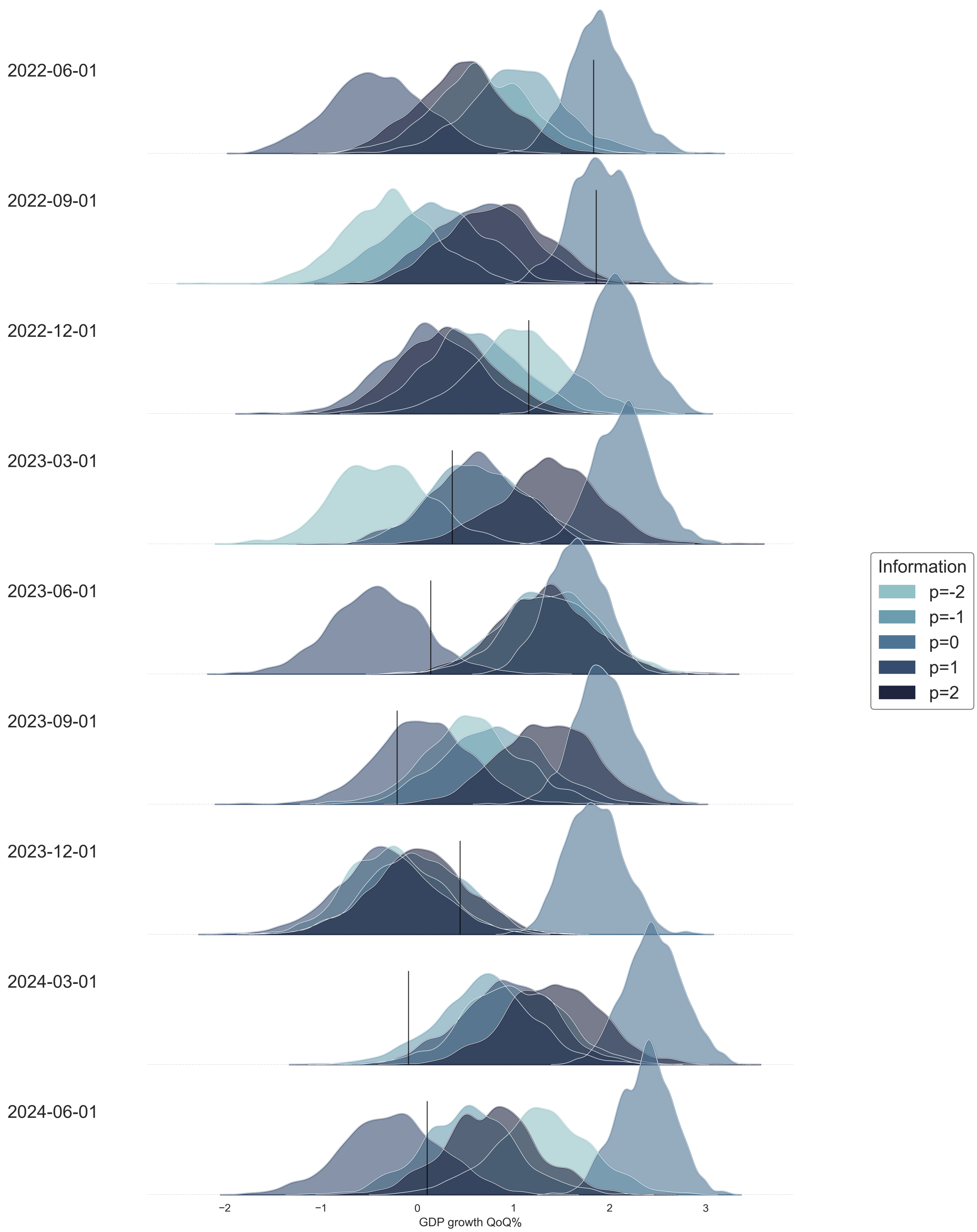
| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline91p5 | 0.60 | 0.70 | 0.92 | 1.06 | 0.80 | 1.06 | 0.58 | 0.86 | 1.06 | 0.88 | 0.80 |
| baseline92 | | 0.42 | 1.25 | 1.39 | 0.51 | 1.37 | 0.72 | 0.71 | 2.72 | 2.72 | 0.60 |
| baseline92p3 | 0.56 | 0.42 | 0.87 | 1.09 | 0.71 | 1.09 | 0.60 | 0.84 | 1.09 | 0.82 | 0.77 |
| baseline92p5 | 0.58 | 0.65 | 0.93 | 1.09 | 0.80 | 1.09 | 0.59 | 0.83 | 1.09 | 0.92 | 0.79 |

**Source:** Own elaboration.
**Notes:** Each specification name encodes four attributes. The prefix indicates the flattening approach: *baseline* uses baseline flattening (three lags); *expanded* applies extended flattening (four or five lags). *baseline** shares the same baseline flattening as *baseline* but is used as a prefix to easily identify the best-performing variable grouping from the pre-selection exercise. The number following the prefix (e.g., 35, 40, 52) identifies the variable grouping. Suffixes *p3* and *p5* indicate PCA retaining 3 or 5 components; *l2* denotes two autoregressive lags of GDP; the absence of these suffixes indicates no dimensionality reduction and no autoregressive lags. *human1* refers to a judgment-based specification constructed by the authors and does not follow this naming convention. See Section 3.2 for a full description of specifications.

## 5.2 Nowcasts

Figure 9 presents the *distribution of nowcast results*. Each curve shows the estimated density for a given vintage, with the observed GDP growth indicated by a vertical line. The figure highlights that, in some quarters, the distributions are tightly concentrated around the observed value, while in other cases, some vintages may produce disperse, noisy predictions. Overall, the distributions tend to fluctuate around the actual GDP growth, despite bias in some periods. These density estimates provide a basis for constructing confidence intervals and computing weighted averages reflecting model accuracy.

Figure 9: Nowcast density by vintage



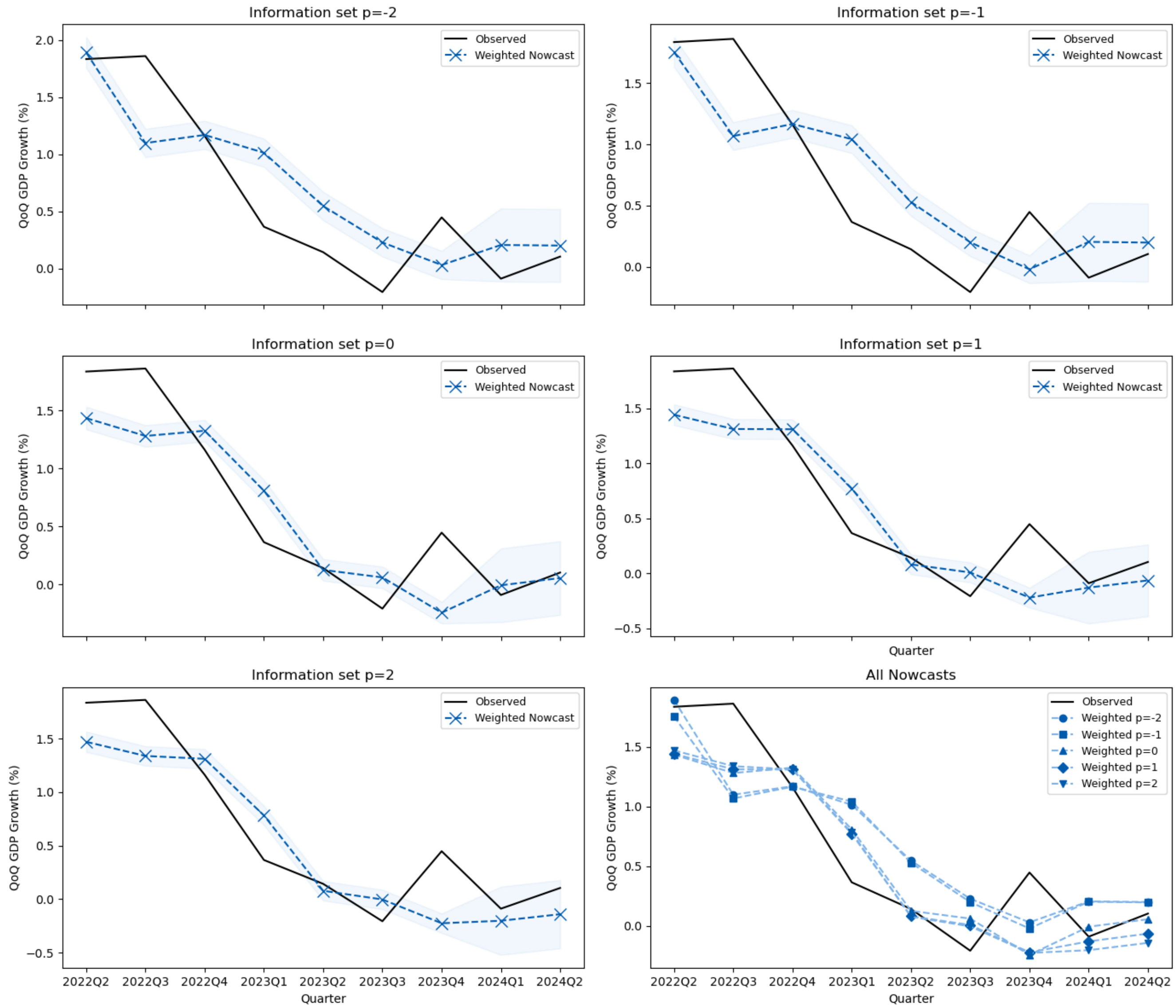

**Source:** Own elaboration.

**Notes:** The figure displays the nowcast density in each test period for the subsample of best-performing models. Information sets are displayed in colors. The vertical line reflects observed GDP growth.

The final set of results is presented in Figure 10. The figure depicts the inverse RMSE-weighted nowcasts generated by all models over the test sample at each vintage, along with the corresponding 95 percent confidence intervals. The figure is organized into six panels. The top-left panel shows results for the information set at $p = -2$, representing estimates based on data available two months before the end of each quarter. The tight confidence intervals in this panel suggest that forecast errors remain within 0.50 percentage points of the realized GDP growth. The top-right panel corresponds to information set $p = -1$, incorporating data available one month before the end of the quarter. The middle panels display results for information sets $p = 0$ (end of quarter) and $p = 1$ (one month after the end of quarter). The bottom left panel presents estimates using information set $p = 2$, including data available two months after the end of the quarter. The bottom right panels includes all weighted nowcasts in all time vintages, as can be seen, nowcast performance improves as more information becomes available.

Across all cases, the nowcasts accurately predict most periods of the sample. Estimates based on early data vintages ($p = -2$ and $p = -1$) tend to slightly overshoot, while nowcasts produced with more recent data are more conservative. Notably, nowcasts from information sets $p = -2$ and $p = -1$ provide accurate predictions for at least four periods, with forecast errors remaining within the confidence intervals. In contrast, the other information sets struggle to accurately predict the earliest observations in the test sample but perform well in subsequent periods. Overall, the weighted nowcasts exhibit trends that closely follow that of the published GDP across information sets.

Figure 10: Test sample nowcast by vintage.




**Source:** Own elaboration.

**Notes:** The figure shows the weighted average of all estimates for each vintage. These estimates are calculated using a subsample of models and specifications with RMSE values below the median for the corresponding publication lag. The weighted average is computed using the inverse RMSE as weights at each publication lag vintage. The 95 percent confidence interval is shaded in gray.

# 6 Concluding remarks

This paper studies a data-driven iterative algorithm to nowcast Bahamian GDP, developing an ensemble of nowcasting estimators to deliver timely and reliable estimates of quarterly

GDP in The Bahamas. We integrate a broad array of econometric and machine learning methods, and structured and unstructured high-frequency near real-time data sources. The proposed approach departs from conventional strategies based on a single model or a single selection of variables. The analysis demonstrates that combining multiple model specifications and filtering based on out-of-sample RMSE performance generates superior nowcasts relative to expert-designed benchmarks, with accuracy improving as more information is incorporated. These findings underscore the value of data-driven, flexible nowcasting tools for real-time economic monitoring in small economies, where conventional statistical systems often lag policy needs.

The empirical results confirm that the nowcasting framework developed in this paper improves the accuracy of GDP growth nowcasts for The Bahamas relative to a human-designed benchmark. Across all information sets, most model specifications yield RMSE values below 0.80 percentage points, with performance improving as more data become available. Filtering out poorly performing models (those with RMSEs above the median in each publication vintage) reduces average forecast errors to 0.72 percentage points — a 29% improvement over the 1.01 RMSE of the human benchmark. Out-of-sample nowcasts often closely capture both the direction and magnitude of GDP growth, especially in post-realization data vintages. Our approach delivers robust performance across all data vintages, indicating that this method effectively exploits the diversity of model specifications and estimation techniques to enhance predictive accuracy in real-time economic monitoring.

Our study has some limitations. First, the nowcasting framework is computationally intensive on first run, with the full set of specifications and estimators requiring several hours of processing. However, once the full model array is estimated, efficiency is improved by filtering out poorly performing models and developing out-of-sample estimates only with the best-performing specifications. Second, the short time span of available data for The Bahamas limits the number of observations available for training and testing, influencing the generalization of model performance, in contrast to data-rich contexts (such as in developed economies) in which larger time spans allow for longer training and testing periods; nevertheless, this limitation will diminish over time as longer time series become available. Third, the COVID-19 pandemic introduced economic disruptions (particularly in the tourism sector), which may have distorted relationships between predictors and GDP during key periods; nonetheless, these irregular years were included in the training sample due to the limited number of time periods, providing information to the models when there are sharp downturns in economic activity. Lastly, the variable selection process using Least Angle Regression (LARS) may be sensitive to the specific versions of Python packages employed.

Differences in computational precision or rounding in iterative RMSE calculations could affect which variables are selected, posing challenges for exact replication across different software environments.

This paper has critical policy implications for small island economies like The Bahamas, where timely and accurate economic estimates are essential for effective decision-making. By leveraging near real-time indicators such as Google Trends and satellite-based Nighttime Lights alongside flexible ensemble nowcasting models, policymakers can obtain early signals of shifts in economic activity, enabling timely responses to changes in capital flows or natural disasters. These methods can serve as tools for cross-validating official statistics, reducing reliance on potentially outdated or misreported indicators (Akbal et al., 2023; Berry et al., 2018). Future research could extend the framework in three directions: (i) sub-national nowcasts capturing inter-island economic dynamics, (ii) sector-specific nowcasts (e.g., tourism, construction), and (iii) nowcasting other macroeconomic variables such as inflation or fiscal balances.

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# 7 Tables

Table 3: Economic indicators

| | No. of series | Publication lag (months) | Frequency | Source |
|---|---|---|---|---|
| **Dependent variable** | | | | |
| Real GDP | 1 | 3 | q | BNSI |
| **Real economy variables (n=150)** | | | | |
| Tourist air arrivals | 35 | 1 | m | MOT |
| Tourist cruise arrivals | 35 | 1 | m | MOT |
| Tourist sea arrivals (excl. cruise) | 35 | 1 | m | MOT |
| Tourist total arrivals | 35 | 1 | m | MOT |
| Construction and energy | 10 | 2 | q | CBOB |
| **Fiscal variables (n=29)** | | | | |
| Central Government revenue | 16 | 2 | m | MOF |
| Central Government expenditure | 11 | 2 | m | MOF |
| Fiscal balance | 2 | 2 | m | MOF |
| **Monetary and financial variables (n=15)** | | | | |
| Credit market indicators | 7 | 0–2 | q, m | CBOB |
| Money supply | 3 | 0–2 | m | CBOB |
| Oil price | 1 | Current | m | EIA |
| Stock market indicators | 4 | 0–2 | m | S&P DJI, NASDAQ, CBOB |
| **External variables (n=22)** | | | | |
| Current account balance | 1 | 2 | q | CBOB |
| Imports by commodity | 11 | 2 | q | CBOB |
| Trade by country | 10 | 1–2 | m | US Census Bureau, Eurostat, ONS, Statistics Canada |
| **Unstructured variables (n=141)** | | | | |
| Google Trends search data | 101 | Current | m | Google Trends |
| Nighttime lights | 40 | Current | m | NASA |

**Source:** Own elaboration.

**Notes:** This table catalogues the economic indicators used in the analysis, categorized by type. For each category, it reports the number of series, typical publication lag, frequency (q: quarterly, m: monthly), and source. The dataset comprises 357 series in total. Source abbreviations: U.S. Energy Information Administration (EIA); S&P Dow Jones Indices (S&P DJI); UK Office for National Statistics (ONS); National Aeronautics and Space Administration (NASA).

Table 4: RMSE across specifications and models (vintage $p = -2$)

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline*52 | | 0.79 | 1.26 | 0.94 | 1.30 | 0.94 | 0.91 | 0.74 | 0.89 | 0.89 | 0.89 |
| baseline*52p3 | 0.91 | 0.60 | 0.87 | 0.74 | 0.60 | 0.74 | 0.52 | 1.00 | 0.74 | 0.82 | 0.74 |
| baseline*52p5 | 0.93 | 0.49 | 0.87 | 0.72 | 0.58 | 0.72 | 0.42 | 1.00 | 0.72 | 0.87 | 0.83 |
| baseline*52p5l2 | | 0.46 | | | | | | 1.00 | | | |
| expanded35 | | | 1.89 | 1.89 | 1.73 | 3.31 | 0.88 | | 0.76 | 0.76 | 0.97 |
| expanded35p3 | | | 1.04 | 0.82 | 0.91 | 1.12 | 0.43 | | 0.82 | 0.58 | 0.79 |
| expanded35p5 | | | 1.06 | 3.35 | 0.87 | 3.66 | 0.40 | | 3.50 | 0.68 | 0.82 |
| expanded35p5l2 | | 0.62 | 1.06 | 3.35 | 0.90 | 3.66 | 0.39 | 1.10 | 3.50 | 0.68 | 0.83 |
| expanded36 | | | 1.94 | 1.43 | 1.75 | 3.05 | 0.88 | | 0.83 | 0.83 | 0.98 |
| expanded36p3 | | | 0.94 | 0.72 | 1.06 | 0.91 | 0.40 | | 0.72 | 0.59 | 0.84 |
| expanded36p5 | | | 0.82 | 1.57 | 1.00 | 3.15 | 0.39 | | 1.49 | 0.72 | 0.82 |
| expanded36p5l2 | | 0.59 | 0.82 | 1.57 | 1.01 | 3.15 | 0.39 | 1.09 | 1.49 | 0.72 | 0.82 |
| expanded37 | | | 1.92 | 1.43 | 1.76 | 3.05 | 0.87 | | 0.83 | 0.83 | 0.98 |
| expanded37p3 | | | 0.94 | 0.72 | 1.04 | 0.91 | 0.45 | | 0.72 | 0.59 | 0.84 |
| expanded37p5 | | | 0.82 | 1.57 | 1.00 | 3.15 | 0.39 | | 1.49 | 0.72 | 0.82 |
| expanded37p5l2 | | 0.59 | 0.83 | 1.57 | 1.01 | 3.15 | 0.40 | 1.04 | 1.49 | 0.72 | 0.82 |
| expanded38 | | | 1.88 | 1.43 | 1.76 | 3.05 | 0.91 | | 0.83 | 0.83 | 0.97 |
| expanded38p3 | | | 0.94 | 0.72 | 1.04 | 0.91 | 0.41 | | 0.72 | 0.59 | 0.84 |
| expanded38p5 | | | 0.82 | 1.57 | 1.00 | 3.15 | 0.37 | | 1.49 | 0.72 | 0.83 |
| expanded38p5l2 | | 0.67 | 0.82 | 1.57 | 1.01 | 3.15 | 0.38 | 1.09 | 1.49 | 0.72 | 0.83 |
| expanded39 | | | 1.86 | 1.43 | 1.76 | 3.05 | 0.85 | | 0.83 | 0.83 | 0.97 |
| expanded39p3 | | | 0.94 | 0.72 | 1.04 | 0.91 | 0.48 | | 0.72 | 0.59 | 0.84 |
| expanded39p5 | | | 0.82 | 1.57 | 0.99 | 3.15 | 0.38 | | 1.49 | 0.72 | 0.82 |
| expanded39p5l2 | | 1.20 | 0.82 | 1.57 | 1.00 | 3.15 | 0.40 | 1.02 | 1.49 | 0.72 | 0.82 |
| expanded40 | | | 1.88 | 1.46 | 1.77 | 2.91 | 0.86 | | 0.81 | 0.81 | 0.97 |
| expanded40p3 | | | 0.87 | 0.79 | 1.04 | 0.85 | 0.49 | | 0.79 | 0.53 | 0.84 |
| expanded40p5 | | | 0.88 | 1.51 | 0.96 | 3.57 | 0.53 | | 2.26 | 0.80 | 0.87 |
| expanded40p5l2 | | 0.91 | 0.88 | 1.51 | 0.95 | 3.57 | 0.47 | 1.00 | 2.26 | 0.80 | 0.86 |
| expanded41 | | | 1.86 | 1.38 | 1.77 | 3.13 | 0.97 | | 0.81 | 0.81 | 0.96 |
| expanded41p3 | | | 0.96 | 1.10 | 0.87 | 1.44 | 0.44 | | 1.10 | 0.76 | 0.73 |
| expanded41p5 | | | 0.70 | 1.72 | 0.92 | 1.27 | 0.48 | | 3.72 | 0.64 | 0.74 |
| expanded41p5l2 | | 0.49 | 0.70 | 1.72 | 0.92 | 1.27 | 0.49 | 0.99 | 3.72 | 0.64 | 0.74 |
| expanded43 | | | 1.55 | 1.35 | 1.70 | 2.07 | 0.85 | | 0.80 | 0.80 | 0.93 |
| expanded43p3 | | | 0.98 | 1.07 | 0.93 | 1.51 | 0.47 | | 1.07 | 0.57 | 0.75 |
| expanded43p5 | | | 0.64 | 1.85 | 1.05 | 1.35 | 0.49 | | 2.78 | 0.63 | 0.84 |
| expanded43p5l2 | | 0.46 | 0.63 | 1.85 | 1.08 | 1.35 | 0.48 | 1.04 | 2.78 | 0.63 | 0.84 |
| expanded44 | | | 1.52 | 1.31 | 1.62 | 1.87 | 0.87 | | 0.84 | 0.84 | 0.92 |
| expanded44p3 | | | 0.88 | 0.96 | 0.87 | 1.49 | 0.49 | | 0.96 | 0.64 | 0.73 |
| expanded44p5 | | | 1.13 | 1.81 | 0.88 | 2.21 | 0.48 | | 2.32 | 0.65 | 0.77 |
| expanded44p5l2 | | 0.46 | 1.10 | 1.81 | 0.89 | 2.21 | 0.48 | 1.03 | 2.32 | 0.65 | 0.78 |
| expanded45 | | | 1.54 | 1.52 | 1.60 | 1.74 | 0.90 | | 0.86 | 0.86 | 0.87 |
| expanded45p3 | | | 1.37 | 1.00 | 0.66 | 1.64 | 0.46 | | 1.00 | 0.56 | 0.79 |
| expanded45p5 | | | 1.00 | 1.74 | 0.62 | 1.40 | 0.48 | | 1.93 | 0.53 | 0.79 |
| expanded45p5l2 | | 0.51 | 1.00 | 1.74 | 0.64 | 1.40 | 0.47 | 1.11 | 1.93 | 0.53 | 0.79 |
| expanded46 | | | 1.49 | 1.51 | 1.61 | 1.76 | 0.87 | | 0.87 | 0.87 | 0.83 |
| expanded46p3 | | | 1.42 | 1.05 | 0.71 | 1.87 | 0.46 | | 1.05 | 0.56 | 0.82 |
| expanded46p5 | | | 1.12 | 1.71 | 0.74 | 1.20 | 0.51 | | 1.81 | 0.53 | 0.83 |
| expanded46p5l2 | | 0.51 | 1.12 | 1.71 | 0.74 | 1.20 | 0.54 | 1.00 | 1.81 | 0.53 | 0.83 |
| expanded47 | | | 1.68 | 1.48 | 1.55 | 1.67 | 0.92 | | 0.89 | 0.89 | 0.83 |
| expanded47p3 | | | 1.18 | 1.01 | 0.71 | 1.72 | 0.46 | | 1.01 | 0.54 | 0.82 |
| expanded47p5 | | | 0.99 | 1.40 | 0.74 | 1.56 | 0.45 | | 1.51 | 0.51 | 0.84 |
| expanded47p5l2 | | 0.52 | 0.97 | 1.40 | 0.73 | 1.56 | 0.47 | 1.00 | 1.51 | 0.51 | 0.84 |
| expanded48 | | | 1.65 | 1.30 | 1.54 | 1.49 | 0.98 | | 0.88 | 0.88 | 0.83 |
| expanded48p3 | | | 0.71 | 0.99 | 0.78 | 0.76 | 0.52 | | 0.99 | 0.58 | 0.83 |
| expanded48p5 | | | 0.55 | 1.35 | 0.74 | 1.80 | 0.44 | | 1.44 | 0.54 | 0.88 |
| expanded48p5l2 | | 0.52 | 0.55 | 1.35 | 0.72 | 1.80 | 0.46 | 1.00 | 1.44 | 0.54 | 0.88 |
| expanded49 | | | 1.46 | 1.30 | 1.60 | 1.42 | 0.82 | | 0.83 | 0.83 | 0.80 |
| expanded49p3 | | | 0.77 | 1.05 | 0.67 | 0.77 | 0.51 | | 1.05 | 0.78 | 0.82 |
| expanded49p5 | | | 0.70 | 1.51 | 0.67 | 1.86 | 0.44 | | 1.57 | 0.53 | 0.88 |
| expanded49p5l2 | | 0.54 | 0.68 | 1.51 | 0.68 | 1.86 | 0.46 | 1.00 | 1.57 | 0.53 | 0.88 |
| expanded50 | | | 1.56 | 1.37 | 1.57 | 1.48 | 0.84 | | 0.83 | 0.83 | 0.79 |
| expanded50p3 | | | 0.67 | 1.01 | 0.71 | 0.86 | 0.59 | | 1.01 | 0.70 | 0.76 |
| expanded50p5 | | | 0.77 | 1.38 | 0.73 | 1.09 | 0.52 | | 1.45 | 0.59 | 0.83 |
| expanded50p5l2 | | 0.49 | 0.77 | 1.38 | 0.74 | 1.09 | 0.50 | 1.07 | 1.45 | 0.59 | 0.83 |
| expanded51 | | | 1.46 | 1.05 | 1.53 | 1.50 | 0.88 | | 0.88 | 0.88 | 0.82 |
| expanded51p3 | | | 0.74 | 0.97 | 0.71 | 0.85 | 0.57 | | 0.97 | 0.71 | 0.75 |
| expanded51p5 | | | 0.90 | 1.27 | 0.66 | 1.92 | 0.45 | | 1.41 | 0.58 | 0.82 |
| expanded51p5l2 | | 1.21 | 0.90 | 1.27 | 0.69 | 1.92 | 0.44 | 1.08 | 1.41 | 0.58 | 0.82 |
| expanded52 | | | 1.45 | 1.01 | 1.15 | 1.43 | 0.88 | | 0.88 | 0.88 | 0.80 |

Continued on next page

**Table 4 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| expanded52p3 | | | 0.59 | 1.02 | 0.39 | 0.81 | 0.51 | | 1.02 | 0.57 | 0.57 |
| expanded52p5 | | | 0.66 | 0.89 | 0.43 | 1.60 | 0.44 | | 0.96 | 0.55 | 0.66 |
| expanded52p5l2 | | | 0.66 | 0.89 | 0.43 | 1.60 | 0.43 | | 0.96 | 0.55 | 0.67 |
| expanded53 | | | 1.50 | 0.98 | 1.15 | 1.26 | 0.88 | | 0.89 | 0.89 | 0.80 |
| expanded53p3 | | | 0.57 | 1.31 | 0.50 | 1.12 | 0.52 | | 1.31 | 0.80 | 0.69 |
| expanded53p5 | | | 0.69 | 1.32 | 0.46 | 1.65 | 0.47 | | 1.31 | 0.69 | 0.79 |
| expanded53p5l2 | | 0.47 | 0.69 | 1.32 | 0.47 | 1.65 | 0.50 | 1.01 | 1.31 | 0.69 | 0.80 |
| expanded54 | | | 1.15 | 0.99 | 0.79 | 1.36 | 0.84 | | 0.89 | 0.89 | 0.74 |
| expanded54p3 | | | 0.77 | 1.47 | 0.62 | 1.07 | 0.52 | | 1.47 | 0.51 | 0.67 |
| expanded54p5 | | | 0.96 | 1.26 | 0.60 | 1.00 | 0.53 | | 1.22 | 0.70 | 0.76 |
| expanded54p5l2 | | 1.17 | 0.96 | 1.26 | 0.59 | 1.00 | 0.50 | 0.94 | 1.22 | 0.70 | 0.75 |
| expanded55 | | | 1.24 | 0.93 | 0.78 | 1.04 | 0.84 | | 0.89 | 0.89 | 0.74 |
| expanded55p3 | | | 0.74 | 1.43 | 0.63 | 1.08 | 0.52 | | 1.43 | 0.62 | 0.70 |
| expanded55p5 | | | 0.79 | 1.49 | 0.61 | 1.01 | 0.56 | | 1.48 | 0.63 | 0.77 |
| expanded55p5l2 | | 1.18 | 0.79 | 1.49 | 0.59 | 1.01 | 0.56 | 0.94 | 1.48 | 0.63 | 0.77 |
| expanded56 | | | 1.19 | 0.94 | 0.79 | 1.00 | 0.81 | | 0.89 | 0.89 | 0.74 |
| expanded56p3 | | | 0.84 | 1.09 | 0.74 | 1.16 | 0.58 | | 1.09 | 0.60 | 0.66 |
| expanded56p5 | | | 0.93 | 1.45 | 0.62 | 0.65 | 0.60 | | 1.46 | 1.20 | 0.73 |
| expanded56p5l2 | | 0.45 | 0.93 | 1.45 | 0.60 | 0.65 | 0.59 | 0.95 | 1.46 | 1.20 | 0.74 |
| expanded57 | | | 1.18 | 0.94 | 0.78 | 1.00 | 0.95 | | 0.89 | 0.89 | 0.74 |
| expanded57p3 | | | 0.83 | 1.09 | 0.78 | 1.16 | 0.56 | | 1.09 | 0.60 | 0.65 |
| expanded57p5 | | | 0.93 | 1.45 | 0.63 | 0.65 | 0.59 | | 1.46 | 1.20 | 0.74 |
| expanded57p5l2 | | 0.47 | 0.92 | 1.45 | 0.63 | 0.65 | 0.62 | 0.95 | 1.46 | 1.20 | 0.74 |
| expanded58 | | | 1.24 | 0.94 | 0.80 | 1.00 | 0.94 | | 0.89 | 0.89 | 0.73 |
| expanded58p3 | | | 0.85 | 1.09 | 0.80 | 1.16 | 0.57 | | 1.09 | 0.60 | 0.65 |
| expanded58p5 | | | 0.93 | 1.45 | 0.61 | 0.65 | 0.59 | | 1.46 | 1.20 | 0.73 |
| expanded58p5l2 | | 1.12 | 0.92 | 1.45 | 0.62 | 0.65 | 0.59 | 0.95 | 1.46 | 1.20 | 0.73 |
| expanded85 | | | 1.19 | 1.06 | 0.77 | 1.07 | 0.83 | | 0.90 | 0.90 | 0.72 |
| expanded85p3 | | | 1.12 | 0.92 | 1.21 | 0.84 | 0.60 | | 0.92 | 0.86 | 0.99 |
| expanded85p5 | | | 0.97 | 0.75 | 0.94 | 0.76 | 0.56 | | 0.80 | 0.74 | 0.94 |
| expanded85p5l2 | | 0.52 | 0.97 | 0.75 | 0.93 | 0.76 | 0.51 | 0.93 | 0.80 | 0.74 | 0.94 |
| expanded87 | | | 1.30 | 1.14 | 0.76 | 1.15 | 0.88 | | 0.90 | 0.90 | 0.74 |
| expanded87p3 | | | 1.12 | 0.96 | 1.24 | 0.85 | 0.58 | | 0.96 | 0.86 | 0.99 |
| expanded87p5 | | | 1.02 | 0.80 | 0.96 | 0.80 | 0.55 | | 0.80 | 0.84 | 0.92 |
| expanded87p5l2 | | 0.51 | 1.03 | 0.80 | 0.97 | 0.80 | 0.58 | 0.91 | 0.80 | 0.84 | 0.92 |
| expanded90 | | | 1.30 | 1.16 | 0.76 | 1.17 | 0.89 | | 1.00 | 1.00 | 0.74 |
| expanded90p3 | | | 1.16 | 0.98 | 0.97 | 0.86 | 0.65 | | 0.97 | 0.90 | 0.99 |
| expanded90p5 | | | 0.89 | 0.80 | 0.90 | 1.00 | 0.56 | | 0.82 | 0.53 | 0.94 |
| expanded90p5l2 | | 0.87 | 0.89 | 0.80 | 0.90 | 1.00 | 0.55 | 0.90 | 0.82 | 0.53 | 0.94 |
| expanded91 | | | 1.17 | 1.15 | 0.72 | 1.14 | 0.90 | | 1.00 | 1.00 | 0.73 |
| expanded91p3 | | | 1.16 | 0.98 | 0.98 | 0.84 | 0.61 | | 0.98 | 0.90 | 0.98 |
| expanded91p5 | | | 1.03 | 0.83 | 0.99 | 1.00 | 0.59 | | 0.84 | 0.64 | 0.94 |
| expanded91p5l2 | | 0.90 | 1.03 | 0.83 | 0.99 | 1.00 | 0.59 | 0.90 | 0.84 | 0.64 | 0.94 |
| expanded92 | | | 1.21 | 1.18 | 0.72 | 1.18 | 0.88 | | 0.99 | 0.99 | 0.73 |
| expanded92p3 | | | 0.99 | 0.95 | 1.05 | 0.85 | 0.57 | | 0.95 | 0.88 | 0.97 |
| expanded92p5 | | | 1.05 | 0.85 | 1.02 | 1.05 | 0.55 | | 0.85 | 0.64 | 0.93 |
| expanded92p5l2 | | 0.80 | 1.04 | 0.85 | 1.02 | 1.05 | 0.56 | 0.88 | 0.85 | 0.64 | 0.92 |
| human1 | 0.83 | 1.22 | 1.41 | 1.30 | 0.86 | 1.07 | 0.46 | | 0.75 | 0.80 | 0.85 |
| baseline35 | | 0.58 | 2.11 | 1.25 | 1.91 | 1.25 | 0.83 | 0.74 | 0.99 | 0.99 | 1.20 |
| baseline35p3 | 1.31 | 0.66 | 1.17 | 0.93 | 1.34 | 0.93 | 0.44 | 1.19 | 0.93 | 1.00 | 1.14 |
| baseline35p5 | 0.75 | 0.63 | 1.20 | 1.16 | 1.17 | 1.16 | 0.38 | 1.10 | 1.22 | 1.00 | 1.13 |
| baseline36 | | 0.57 | 2.02 | 1.56 | 1.91 | 1.56 | 0.81 | 0.74 | 0.99 | 0.99 | 1.19 |
| baseline36p3 | 1.41 | 0.64 | 1.16 | 0.89 | 1.26 | 0.89 | 0.43 | 1.20 | 0.89 | 1.00 | 1.16 |
| baseline36p5 | 0.82 | 0.65 | 1.36 | 1.03 | 1.18 | 1.03 | 0.39 | 1.09 | 1.03 | 1.08 | 1.12 |
| baseline37 | | 0.57 | 1.98 | 1.56 | 1.94 | 1.56 | 0.91 | 0.74 | 0.99 | 0.99 | 1.19 |
| baseline37p3 | 1.48 | 0.60 | 1.16 | 0.89 | 1.27 | 0.89 | 0.42 | 1.22 | 0.89 | 1.00 | 1.15 |
| baseline37p5 | 0.86 | 0.61 | 1.36 | 1.03 | 1.18 | 1.03 | 0.43 | 1.04 | 1.03 | 1.08 | 1.13 |
| baseline38 | | 0.57 | 2.03 | 1.56 | 1.94 | 1.56 | 0.85 | 0.75 | 0.99 | 0.99 | 1.21 |
| baseline38p3 | 1.38 | 0.49 | 1.16 | 0.89 | 1.28 | 0.89 | 0.42 | 1.22 | 0.89 | 1.00 | 1.15 |
| baseline38p5 | 0.87 | 0.58 | 1.36 | 1.03 | 1.20 | 1.03 | 0.41 | 1.09 | 1.03 | 1.08 | 1.13 |
| baseline39 | | 0.57 | 2.05 | 1.56 | 1.93 | 1.56 | 0.83 | 0.74 | 0.99 | 0.99 | 1.20 |
| baseline39p3 | 1.42 | 0.49 | 1.16 | 0.89 | 1.27 | 0.89 | 0.44 | 1.09 | 0.89 | 1.00 | 1.15 |
| baseline39p5 | 0.84 | 0.53 | 1.36 | 1.03 | 1.19 | 1.03 | 0.41 | 1.02 | 1.03 | 1.08 | 1.12 |
| baseline40 | | 0.95 | 2.01 | 1.86 | 1.93 | 1.86 | 0.80 | 0.73 | 0.98 | 0.98 | 1.20 |
| baseline40p3 | 1.36 | 0.49 | 1.25 | 0.88 | 1.35 | 0.88 | 0.44 | 1.10 | 0.88 | 1.00 | 1.15 |
| baseline40p5 | 0.83 | 0.55 | 1.42 | 1.40 | 1.14 | 1.40 | 0.50 | 1.00 | 1.41 | 1.14 | 1.15 |
| baseline41 | | 0.95 | 2.03 | 1.61 | 1.93 | 1.61 | 0.91 | 0.74 | 0.98 | 0.98 | 1.18 |
| baseline41p3 | 0.81 | 0.68 | 1.21 | 0.83 | 1.21 | 0.83 | 0.42 | 1.06 | 0.83 | 0.99 | 1.06 |
| baseline41p5 | 0.75 | 0.49 | 1.26 | 0.96 | 1.22 | 0.96 | 0.46 | 0.99 | 0.95 | 1.01 | 1.03 |
| baseline43 | | 0.95 | 1.52 | 1.45 | 1.89 | 1.45 | 0.90 | 0.76 | 0.88 | 0.88 | 1.14 |

Continued on next page

**Table 4 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline43p3 | 1.19 | 0.58 | 1.13 | 0.79 | 1.08 | 0.79 | 0.47 | 1.04 | 0.79 | 0.97 | 1.01 |
| baseline43p5 | 1.08 | 0.46 | 1.18 | 0.75 | 1.09 | 0.75 | 0.47 | 1.04 | 0.75 | 0.96 | 1.02 |
| baseline44 | | 0.94 | 1.44 | 1.47 | 1.76 | 1.47 | 0.87 | 0.76 | 0.87 | 0.87 | 1.12 |
| baseline44p3 | 1.02 | 0.56 | 1.04 | 0.82 | 1.00 | 0.82 | 0.51 | 1.04 | 0.82 | 0.97 | 0.97 |
| baseline44p5 | 1.13 | 0.46 | 1.04 | 0.97 | 0.94 | 0.97 | 0.53 | 1.03 | 0.97 | 1.01 | 0.98 |
| baseline45 | | 0.94 | 1.38 | 1.79 | 1.74 | 1.79 | 0.98 | 0.75 | 0.87 | 0.87 | 1.03 |
| baseline45p3 | 1.15 | 0.54 | 0.77 | 0.77 | 0.78 | 0.77 | 0.46 | 1.11 | 0.77 | 0.96 | 0.91 |
| baseline45p5 | 1.15 | 0.51 | 0.79 | 0.80 | 0.78 | 0.80 | 0.49 | 1.11 | 0.80 | 0.99 | 0.96 |
| baseline46 | | 0.93 | 1.37 | 1.78 | 1.73 | 1.78 | 0.92 | 0.75 | 0.87 | 0.87 | 0.97 |
| baseline46p3 | 1.27 | 0.63 | 0.90 | 0.76 | 0.73 | 0.76 | 0.46 | 0.99 | 0.76 | 0.95 | 0.90 |
| baseline46p5 | 1.09 | 0.50 | 0.97 | 0.74 | 0.67 | 0.74 | 0.52 | 1.00 | 0.74 | 0.98 | 0.96 |
| baseline47 | | 0.93 | 1.31 | 1.62 | 1.69 | 1.62 | 0.94 | 0.75 | 0.88 | 0.88 | 0.94 |
| baseline47p3 | 1.21 | 0.58 | 0.95 | 0.72 | 0.74 | 0.72 | 0.45 | 0.99 | 0.72 | 0.92 | 0.90 |
| baseline47p5 | 1.11 | 0.53 | 1.00 | 0.76 | 0.70 | 0.76 | 0.45 | 1.00 | 0.75 | 0.95 | 0.95 |
| baseline48 | | 0.93 | 1.39 | 1.35 | 1.70 | 1.35 | 0.89 | 0.75 | 0.88 | 0.88 | 0.93 |
| baseline48p3 | 1.21 | 0.57 | 0.91 | 0.73 | 0.74 | 0.73 | 0.52 | 1.01 | 0.73 | 0.92 | 0.88 |
| baseline48p5 | 1.14 | 0.54 | 0.68 | 0.78 | 0.70 | 0.78 | 0.46 | 1.00 | 0.77 | 0.94 | 0.94 |
| baseline49 | | 0.93 | 1.26 | 1.34 | 1.72 | 1.34 | 0.91 | 0.74 | 0.88 | 0.88 | 0.92 |
| baseline49p3 | 1.17 | 0.57 | 1.12 | 0.70 | 0.77 | 0.70 | 0.53 | 1.02 | 0.70 | 0.91 | 0.91 |
| baseline49p5 | 1.03 | 0.57 | 1.00 | 0.69 | 0.70 | 0.69 | 0.43 | 1.00 | 0.68 | 0.92 | 0.96 |
| baseline50 | | 0.93 | 1.25 | 1.43 | 1.67 | 1.43 | 0.88 | 0.73 | 0.89 | 0.89 | 0.91 |
| baseline50p3 | 0.92 | 0.94 | 0.64 | 0.74 | 0.72 | 0.74 | 0.60 | 1.07 | 0.74 | 0.92 | 0.90 |
| baseline50p5 | 0.96 | 0.53 | 0.80 | 0.68 | 0.68 | 0.68 | 0.49 | 1.07 | 0.67 | 0.93 | 0.97 |
| baseline51 | | 0.89 | 1.21 | 0.94 | 1.64 | 0.94 | 0.81 | 0.73 | 0.90 | 0.90 | 0.91 |
| baseline51p3 | 0.98 | 0.59 | 0.70 | 0.76 | 0.66 | 0.76 | 0.54 | 1.09 | 0.76 | 0.91 | 0.87 |
| baseline51p5 | 0.94 | 0.54 | 0.81 | 0.66 | 0.68 | 0.66 | 0.43 | 1.08 | 0.66 | 0.93 | 0.95 |
| baseline53 | | 0.81 | 1.22 | 0.95 | 1.27 | 0.96 | 0.90 | 0.74 | 0.89 | 0.89 | 0.89 |
| baseline53p3 | 1.01 | 0.59 | 0.71 | 0.78 | 0.41 | 0.78 | 0.51 | 1.00 | 0.78 | 0.85 | 0.79 |
| baseline53p5 | 0.92 | 0.50 | 0.96 | 0.76 | 0.44 | 0.76 | 0.49 | 1.01 | 0.76 | 0.90 | 0.87 |
| baseline54 | | 0.76 | 1.38 | 0.98 | 0.79 | 0.98 | 0.87 | 0.75 | 0.89 | 0.89 | 0.81 |
| baseline54p3 | 0.89 | 0.58 | 0.70 | 0.76 | 0.73 | 0.76 | 0.54 | 0.94 | 0.76 | 0.85 | 0.78 |
| baseline54p5 | 0.98 | 0.49 | 0.93 | 0.75 | 0.75 | 0.75 | 0.50 | 0.94 | 0.75 | 0.90 | 0.87 |
| baseline55 | | 0.86 | 1.47 | 0.99 | 0.80 | 0.99 | 0.87 | 0.75 | 0.89 | 0.89 | 0.82 |
| baseline55p3 | 0.94 | 0.57 | 0.71 | 0.77 | 0.78 | 0.77 | 0.55 | 0.94 | 0.77 | 0.85 | 0.79 |
| baseline55p5 | 0.90 | 1.09 | 0.93 | 0.78 | 0.82 | 0.78 | 0.54 | 0.94 | 0.78 | 0.92 | 0.87 |
| baseline56 | | 0.71 | 1.45 | 1.00 | 0.79 | 1.01 | 0.88 | 0.74 | 0.89 | 0.89 | 0.82 |
| baseline56p3 | 0.81 | 0.58 | 1.08 | 0.78 | 0.78 | 0.78 | 0.58 | 0.92 | 0.78 | 0.85 | 0.74 |
| baseline56p5 | 0.87 | 0.50 | 1.11 | 0.76 | 0.76 | 0.76 | 0.59 | 0.95 | 0.76 | 0.89 | 0.82 |
| baseline57 | | 0.71 | 1.43 | 1.00 | 0.80 | 1.01 | 0.93 | 0.74 | 0.89 | 0.89 | 0.81 |
| baseline57p3 | 0.93 | 0.58 | 1.08 | 0.78 | 0.78 | 0.78 | 0.57 | 0.92 | 0.78 | 0.85 | 0.74 |
| baseline57p5 | 0.88 | 0.50 | 1.11 | 0.76 | 0.77 | 0.76 | 0.56 | 0.95 | 0.76 | 0.89 | 0.83 |
| baseline58 | | 0.71 | 1.41 | 1.00 | 0.79 | 1.01 | 0.88 | 0.74 | 0.89 | 0.89 | 0.82 |
| baseline58p3 | 0.85 | 0.58 | 1.08 | 0.78 | 0.78 | 0.78 | 0.55 | 0.92 | 0.78 | 0.85 | 0.74 |
| baseline58p5 | 0.88 | 0.50 | 1.11 | 0.76 | 0.77 | 0.76 | 0.63 | 0.95 | 0.76 | 0.89 | 0.83 |
| baseline85 | | 0.53 | 1.36 | 1.08 | 0.79 | 1.08 | 0.81 | 0.76 | 1.00 | 1.00 | 0.81 |
| baseline85p3 | 0.78 | 0.48 | 1.10 | 1.03 | 0.83 | 1.03 | 0.61 | 0.89 | 1.03 | 0.92 | 1.00 |
| baseline85p5 | 0.79 | 0.52 | 0.94 | 0.91 | 0.77 | 0.91 | 0.51 | 0.93 | 0.91 | 0.95 | 1.01 |
| baseline87 | | 0.52 | 1.38 | 1.18 | 0.77 | 1.18 | 0.88 | 0.76 | 1.01 | 1.01 | 0.83 |
| baseline87p3 | 0.75 | 0.49 | 1.10 | 1.03 | 0.85 | 1.03 | 0.59 | 0.87 | 1.03 | 0.92 | 1.00 |
| baseline87p5 | 0.80 | 0.51 | 1.12 | 0.91 | 0.92 | 0.91 | 0.59 | 0.91 | 0.91 | 0.81 | 1.02 |
| baseline90 | | 0.58 | 1.37 | 1.19 | 0.76 | 1.19 | 0.92 | 0.75 | 1.01 | 1.01 | 0.84 |
| baseline90p3 | 0.70 | 0.45 | 0.92 | 1.03 | 0.72 | 1.03 | 0.61 | 0.87 | 1.03 | 0.93 | 0.96 |
| baseline90p5 | 0.78 | 0.89 | 0.94 | 0.94 | 0.81 | 0.94 | 0.56 | 0.90 | 0.94 | 0.81 | 1.00 |
| baseline91 | | 0.53 | 1.40 | 1.16 | 0.77 | 1.16 | 0.88 | 0.75 | 1.01 | 1.01 | 0.83 |
| baseline91p3 | 0.72 | 0.45 | 0.91 | 1.03 | 0.75 | 1.03 | 0.61 | 0.88 | 1.03 | 0.93 | 0.95 |
| baseline91p5 | 0.78 | 0.92 | 0.97 | 0.94 | 0.88 | 0.94 | 0.57 | 0.90 | 0.94 | 0.83 | 1.00 |
| baseline92 | | 0.60 | 1.41 | 1.19 | 0.76 | 1.19 | 0.84 | 0.75 | 1.01 | 1.01 | 0.84 |
| baseline92p3 | 0.74 | 0.46 | 0.70 | 1.06 | 0.91 | 1.06 | 0.61 | 0.85 | 1.06 | 0.94 | 0.98 |
| baseline92p5 | 0.80 | 0.82 | 1.05 | 0.97 | 0.93 | 0.97 | 0.58 | 0.88 | 0.97 | 0.84 | 1.02 |

**Source:** Own elaboration.

**Notes:** Each specification name encodes four attributes. The prefix indicates the flattening approach: *baseline* uses baseline flattening (three lags); *expanded* applies extended flattening (four or five lags). *baseline** shares the same baseline flattening as *baseline* but is used as a prefix to easily identify the best-performing variable grouping from the pre-selection exercise. The number following the prefix (e.g., 35, 40, 52) identifies the variable grouping. Suffixes *p3* and *p5* indicate PCA retaining 3 or 5 components; *l2* denotes two autoregressive lags of GDP; the absence of these suffixes indicates no dimensionality reduction and no autoregressive lags. *human1* refers to a judgment-based specification constructed by the authors and does not follow this naming convention. See Section 3.2 for a full description of specifications.

Table 5: RMSE across specifications and models (vintage $p = -1$)

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline*52 | | 0.79 | 1.50 | 1.01 | 1.28 | 1.01 | 0.76 | 0.74 | 1.13 | 1.13 | 0.82 |
| baseline*52p3 | 0.73 | 0.65 | 0.68 | 1.56 | 0.90 | 1.56 | 0.52 | 1.04 | 1.56 | 0.80 | 0.78 |
| baseline*52p5 | 0.86 | 0.50 | 0.70 | 1.87 | 0.95 | 1.87 | 0.48 | 1.02 | 1.88 | 0.86 | 0.84 |
| baseline*52p5l2 | | 0.47 | | | | | | 1.02 | | | |
| expanded35 | | | 1.70 | 1.56 | 1.56 | 3.20 | 0.71 | | 0.78 | 0.78 | 0.87 |
| expanded35p3 | | | 0.87 | 1.07 | 1.05 | 0.85 | 0.56 | | 1.07 | 0.82 | 0.83 |
| expanded35p5 | | | 0.89 | 3.58 | 0.90 | 3.53 | 0.47 | | 6.40 | 0.81 | 0.88 |
| expanded35p5l2 | | 0.63 | 0.89 | 3.58 | 0.95 | 3.53 | 0.46 | 1.23 | 6.40 | 0.81 | 0.89 |
| expanded36 | | | 1.75 | 0.95 | 1.58 | 2.87 | 0.73 | | 1.02 | 1.02 | 0.90 |
| expanded36p3 | | | 0.94 | 1.16 | 1.18 | 0.89 | 0.55 | | 1.16 | 0.92 | 0.85 |
| expanded36p5 | | | 0.82 | 3.71 | 1.08 | 3.23 | 0.37 | | 7.48 | 0.68 | 0.84 |
| expanded36p5l2 | | 0.60 | 0.82 | 3.71 | 1.07 | 3.23 | 0.37 | 1.22 | 7.48 | 0.68 | 0.84 |
| expanded37 | | | 1.72 | 0.95 | 1.59 | 2.87 | 0.74 | | 1.02 | 1.02 | 0.90 |
| expanded37p3 | | | 0.94 | 1.16 | 1.15 | 0.89 | 0.58 | | 1.16 | 0.92 | 0.85 |
| expanded37p5 | | | 0.81 | 3.71 | 1.09 | 3.23 | 0.36 | | 7.48 | 0.68 | 0.84 |
| expanded37p5l2 | | 0.63 | 0.82 | 3.71 | 1.09 | 3.23 | 0.39 | 1.16 | 7.48 | 0.68 | 0.84 |
| expanded38 | | | 1.71 | 0.95 | 1.58 | 2.87 | 0.78 | | 1.02 | 1.02 | 0.90 |
| expanded38p3 | | | 0.94 | 1.16 | 1.18 | 0.89 | 0.59 | | 1.16 | 0.92 | 0.85 |
| expanded38p5 | | | 0.81 | 3.71 | 1.09 | 3.23 | 0.36 | | 7.48 | 0.68 | 0.85 |
| expanded38p5l2 | | 0.67 | 0.82 | 3.71 | 1.08 | 3.23 | 0.35 | 1.21 | 7.48 | 0.68 | 0.85 |
| expanded39 | | | 1.69 | 0.95 | 1.60 | 2.87 | 0.72 | | 1.02 | 1.02 | 0.89 |
| expanded39p3 | | | 0.94 | 1.16 | 1.16 | 0.89 | 0.63 | | 1.16 | 0.92 | 0.85 |
| expanded39p5 | | | 0.81 | 3.71 | 1.06 | 3.23 | 0.36 | | 7.48 | 0.68 | 0.84 |
| expanded39p5l2 | | 1.19 | 0.81 | 3.71 | 1.07 | 3.23 | 0.38 | 1.07 | 7.48 | 0.68 | 0.83 |
| expanded40 | | | 1.70 | 1.16 | 1.61 | 2.87 | 0.72 | | 0.93 | 0.93 | 0.90 |
| expanded40p3 | | | 0.84 | 1.25 | 1.12 | 1.06 | 0.63 | | 1.25 | 0.92 | 0.85 |
| expanded40p5 | | | 0.78 | 2.82 | 1.02 | 2.22 | 0.34 | | 3.83 | 0.62 | 0.84 |
| expanded40p5l2 | | 0.91 | 0.78 | 2.82 | 1.00 | 2.22 | 0.27 | 1.05 | 3.83 | 0.62 | 0.84 |
| expanded41 | | | 1.69 | 1.11 | 1.60 | 3.10 | 0.83 | | 0.93 | 0.93 | 0.89 |
| expanded41p3 | | | 1.06 | 1.60 | 0.86 | 1.70 | 0.46 | | 1.60 | 0.82 | 0.72 |
| expanded41p5 | | | 0.77 | 2.33 | 0.90 | 1.72 | 0.48 | | 5.95 | 0.55 | 0.77 |
| expanded41p5l2 | | 0.50 | 0.77 | 2.33 | 0.91 | 1.72 | 0.49 | 1.02 | 5.95 | 0.55 | 0.77 |
| expanded43 | | | 1.48 | 1.14 | 1.54 | 2.07 | 0.74 | | 0.94 | 0.94 | 0.85 |
| expanded43p3 | | | 1.00 | 1.14 | 1.16 | 1.99 | 0.50 | | 1.14 | 0.70 | 0.80 |
| expanded43p5 | | | 1.03 | 1.78 | 1.33 | 2.31 | 0.46 | | 2.57 | 0.87 | 0.84 |
| expanded43p5l2 | | 0.47 | 1.03 | 1.78 | 1.31 | 2.31 | 0.44 | 1.09 | 2.57 | 0.87 | 0.83 |
| expanded44 | | | 1.46 | 1.17 | 1.50 | 1.93 | 0.70 | | 1.01 | 1.01 | 0.84 |
| expanded44p3 | | | 0.95 | 1.51 | 1.18 | 2.05 | 0.54 | | 1.51 | 0.71 | 0.79 |
| expanded44p5 | | | 1.15 | 2.38 | 1.25 | 1.78 | 0.41 | | 4.57 | 0.83 | 0.79 |
| expanded44p5l2 | | 0.46 | 1.12 | 2.38 | 1.27 | 1.78 | 0.45 | 1.08 | 4.57 | 0.83 | 0.80 |
| expanded45 | | | 1.46 | 1.24 | 1.46 | 1.56 | 0.74 | | 1.04 | 1.04 | 0.81 |
| expanded45p3 | | | 1.40 | 1.31 | 1.01 | 1.96 | 0.46 | | 1.31 | 0.66 | 0.91 |
| expanded45p5 | | | 1.01 | 1.62 | 1.01 | 1.51 | 0.44 | | 2.42 | 0.59 | 0.87 |
| expanded45p5l2 | | 0.52 | 1.01 | 1.62 | 1.02 | 1.51 | 0.45 | 1.19 | 2.42 | 0.59 | 0.87 |
| expanded46 | | | 1.45 | 1.23 | 1.47 | 1.57 | 0.69 | | 1.06 | 1.06 | 0.78 |
| expanded46p3 | | | 1.48 | 1.28 | 1.15 | 1.94 | 0.45 | | 1.28 | 0.63 | 0.97 |
| expanded46p5 | | | 1.12 | 1.49 | 1.27 | 1.50 | 0.46 | | 1.36 | 0.59 | 0.92 |
| expanded46p5l2 | | 0.53 | 1.12 | 1.49 | 1.26 | 1.50 | 0.50 | 1.07 | 1.36 | 0.59 | 0.92 |
| expanded47 | | | 1.79 | 1.10 | 1.40 | 1.39 | 0.80 | | 1.08 | 1.08 | 0.77 |
| expanded47p3 | | | 1.32 | 1.25 | 1.10 | 1.92 | 0.42 | | 1.25 | 0.60 | 0.97 |
| expanded47p5 | | | 1.12 | 1.44 | 1.25 | 1.43 | 0.43 | | 1.27 | 0.57 | 0.93 |
| expanded47p5l2 | | 0.54 | 1.08 | 1.44 | 1.25 | 1.43 | 0.45 | 1.06 | 1.27 | 0.57 | 0.93 |
| expanded48 | | | 1.81 | 1.19 | 1.38 | 1.56 | 0.84 | | 1.08 | 1.08 | 0.77 |
| expanded48p3 | | | 1.07 | 1.29 | 1.17 | 1.77 | 0.49 | | 1.29 | 0.65 | 0.98 |
| expanded48p5 | | | 1.07 | 1.01 | 1.21 | 1.19 | 0.46 | | 0.86 | 0.61 | 0.98 |
| expanded48p5l2 | | 0.53 | 1.08 | 1.01 | 1.22 | 1.19 | 0.48 | 1.06 | 0.86 | 0.61 | 0.99 |
| expanded49 | | | 1.64 | 1.17 | 1.44 | 1.43 | 0.66 | | 0.98 | 0.98 | 0.74 |
| expanded49p3 | | | 1.03 | 1.02 | 1.00 | 1.38 | 0.47 | | 1.02 | 0.70 | 0.93 |
| expanded49p5 | | | 1.07 | 0.96 | 1.02 | 1.04 | 0.45 | | 0.85 | 0.57 | 0.95 |
| expanded49p5l2 | | 0.55 | 1.08 | 0.96 | 1.04 | 1.04 | 0.46 | 1.06 | 0.85 | 0.57 | 0.95 |
| expanded50 | | | 1.71 | 1.18 | 1.43 | 1.37 | 0.72 | | 0.97 | 0.97 | 0.74 |
| expanded50p3 | | | 0.61 | 1.22 | 1.07 | 1.62 | 0.52 | | 1.22 | 0.71 | 0.81 |
| expanded50p5 | | | 0.76 | 1.13 | 1.19 | 0.80 | 0.53 | | 1.29 | 0.72 | 0.88 |
| expanded50p5l2 | | 0.51 | 0.76 | 1.13 | 1.18 | 0.80 | 0.49 | 1.12 | 1.29 | 0.72 | 0.87 |
| expanded51 | | | 1.61 | 1.03 | 1.41 | 1.51 | 0.70 | | 1.07 | 1.07 | 0.77 |
| expanded51p3 | | | 0.67 | 1.28 | 1.06 | 1.64 | 0.52 | | 1.28 | 0.72 | 0.80 |
| expanded51p5 | | | 0.90 | 0.98 | 1.12 | 0.87 | 0.49 | | 0.96 | 0.73 | 0.87 |
| expanded51p5l2 | | 1.16 | 0.90 | 0.98 | 1.13 | 0.87 | 0.50 | 1.14 | 0.96 | 0.73 | 0.87 |
| expanded52 | | | 1.62 | 1.06 | 1.15 | 1.50 | 0.71 | | 1.07 | 1.07 | 0.74 |

Continued on next page

Table 5 – continued

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| expanded52p3 | | | 0.60 | 1.34 | 0.65 | 1.96 | 0.51 | | 1.34 | 0.69 | 0.67 |
| expanded52p5 | | | 0.61 | 0.99 | 0.85 | 0.66 | 0.50 | | 1.15 | 0.68 | 0.75 |
| expanded52p5l2 | | | 0.61 | 0.99 | 0.83 | 0.66 | 0.49 | | 1.15 | 0.68 | 0.76 |
| expanded53 | | | 1.62 | 0.94 | 1.13 | 1.24 | 0.74 | | 1.07 | 1.07 | 0.73 |
| expanded53p3 | | | 0.62 | 1.45 | 0.72 | 1.70 | 0.51 | | 1.45 | 1.11 | 0.73 |
| expanded53p5 | | | 0.64 | 1.11 | 0.71 | 0.53 | 0.50 | | 1.14 | 0.83 | 0.83 |
| expanded53p5l2 | | 0.49 | 0.65 | 1.11 | 0.72 | 0.53 | 0.54 | 1.05 | 1.14 | 0.83 | 0.84 |
| expanded54 | | | 1.36 | 0.97 | 0.75 | 1.36 | 0.70 | | 1.07 | 1.07 | 0.68 |
| expanded54p3 | | | 0.86 | 1.53 | 0.76 | 1.49 | 0.52 | | 1.53 | 1.25 | 0.70 |
| expanded54p5 | | | 0.96 | 1.24 | 0.71 | 0.34 | 0.53 | | 1.27 | 0.87 | 0.81 |
| expanded54p5l2 | | 1.14 | 0.96 | 1.24 | 0.67 | 0.34 | 0.49 | 0.94 | 1.27 | 0.87 | 0.80 |
| expanded55 | | | 1.49 | 0.90 | 0.75 | 1.03 | 0.68 | | 1.07 | 1.07 | 0.68 |
| expanded55p3 | | | 0.64 | 1.50 | 0.74 | 1.57 | 0.53 | | 1.50 | 0.71 | 0.72 |
| expanded55p5 | | | 0.79 | 1.60 | 0.67 | 1.48 | 0.60 | | 1.58 | 0.86 | 0.81 |
| expanded55p5l2 | | 1.15 | 0.79 | 1.60 | 0.67 | 1.48 | 0.61 | 0.94 | 1.58 | 0.86 | 0.81 |
| expanded56 | | | 1.43 | 0.97 | 0.74 | 1.04 | 0.67 | | 1.07 | 1.07 | 0.68 |
| expanded56p3 | | | 0.81 | 1.52 | 0.97 | 1.52 | 0.58 | | 1.52 | 0.71 | 0.69 |
| expanded56p5 | | | 0.94 | 1.48 | 0.65 | 1.34 | 0.61 | | 1.51 | 1.17 | 0.76 |
| expanded56p5l2 | | 0.48 | 0.94 | 1.48 | 0.63 | 1.34 | 0.63 | 0.93 | 1.51 | 1.17 | 0.76 |
| expanded57 | | | 1.39 | 0.97 | 0.73 | 1.04 | 0.79 | | 1.07 | 1.07 | 0.68 |
| expanded57p3 | | | 0.82 | 1.52 | 0.98 | 1.52 | 0.56 | | 1.52 | 0.71 | 0.68 |
| expanded57p5 | | | 0.94 | 1.48 | 0.65 | 1.34 | 0.61 | | 1.51 | 1.17 | 0.76 |
| expanded57p5l2 | | 0.50 | 0.95 | 1.48 | 0.65 | 1.34 | 0.63 | 0.93 | 1.51 | 1.17 | 0.76 |
| expanded58 | | | 1.47 | 0.97 | 0.74 | 1.04 | 0.77 | | 1.07 | 1.07 | 0.67 |
| expanded58p3 | | | 0.83 | 1.52 | 1.02 | 1.52 | 0.58 | | 1.52 | 0.71 | 0.68 |
| expanded58p5 | | | 0.93 | 1.48 | 0.62 | 1.34 | 0.60 | | 1.51 | 1.17 | 0.76 |
| expanded58p5l2 | | 1.09 | 0.94 | 1.48 | 0.64 | 1.34 | 0.61 | 0.93 | 1.51 | 1.17 | 0.76 |
| expanded85 | | | 1.38 | 1.19 | 0.71 | 1.16 | 0.69 | | 1.00 | 1.00 | 0.65 |
| expanded85p3 | | | 1.04 | 1.98 | 1.09 | 1.77 | 0.61 | | 2.13 | 0.84 | 0.87 |
| expanded85p5 | | | 0.85 | 0.99 | 0.89 | 0.76 | 0.58 | | 1.12 | 0.95 | 0.87 |
| expanded85p5l2 | | 0.52 | 0.86 | 0.99 | 0.90 | 0.76 | 0.52 | 0.93 | 1.12 | 0.95 | 0.87 |
| expanded87 | | | 1.42 | 1.11 | 0.71 | 1.12 | 0.73 | | 1.00 | 1.00 | 0.67 |
| expanded87p3 | | | 1.01 | 1.47 | 0.99 | 1.09 | 0.58 | | 1.62 | 0.91 | 0.88 |
| expanded87p5 | | | 0.89 | 0.83 | 0.91 | 0.74 | 0.56 | | 0.92 | 0.87 | 0.83 |
| expanded87p5l2 | | 0.51 | 0.89 | 0.83 | 0.93 | 0.74 | 0.59 | 0.92 | 0.92 | 0.87 | 0.84 |
| expanded90 | | | 1.41 | 1.12 | 0.72 | 1.13 | 0.71 | | 1.10 | 1.10 | 0.66 |
| expanded90p3 | | | 1.16 | 1.06 | 0.78 | 0.81 | 0.67 | | 1.09 | 0.88 | 0.88 |
| expanded90p5 | | | 0.92 | 0.90 | 0.71 | 0.97 | 0.58 | | 0.96 | 0.84 | 0.84 |
| expanded90p5l2 | | 0.87 | 0.91 | 0.90 | 0.73 | 0.97 | 0.57 | 0.90 | 0.96 | 0.84 | 0.85 |
| expanded91 | | | 1.31 | 1.13 | 0.68 | 1.13 | 0.74 | | 1.10 | 1.10 | 0.66 |
| expanded91p3 | | | 1.16 | 1.04 | 0.76 | 0.84 | 0.65 | | 1.07 | 0.88 | 0.88 |
| expanded91p5 | | | 1.05 | 1.02 | 0.79 | 0.90 | 0.62 | | 1.07 | 0.66 | 0.87 |
| expanded91p5l2 | | 0.91 | 1.05 | 1.02 | 0.79 | 0.90 | 0.60 | 0.90 | 1.07 | 0.66 | 0.87 |
| expanded92 | | | 1.33 | 1.16 | 0.67 | 1.16 | 0.73 | | 1.09 | 1.09 | 0.65 |
| expanded92p3 | | | 1.01 | 0.93 | 0.80 | 0.89 | 0.60 | | 0.94 | 0.89 | 0.86 |
| expanded92p5 | | | 1.05 | 1.12 | 0.77 | 0.94 | 0.57 | | 1.21 | 0.67 | 0.85 |
| expanded92p5l2 | | 0.82 | 1.04 | 1.12 | 0.76 | 0.94 | 0.57 | 0.88 | 1.21 | 0.67 | 0.85 |
| human1 | 0.62 | 0.97 | 1.36 | 1.13 | 0.94 | 0.96 | 0.50 | | 0.96 | 1.18 | 0.80 |
| baseline35 | | 0.53 | 1.62 | 1.11 | 1.70 | 1.11 | 0.68 | 0.74 | 1.31 | 1.31 | 1.04 |
| baseline35p3 | 1.62 | 0.66 | 0.61 | 1.43 | 1.27 | 1.43 | 0.55 | 1.35 | 1.43 | 1.08 | 1.03 |
| baseline35p5 | 1.04 | 0.63 | 0.68 | 3.16 | 1.19 | 3.17 | 0.46 | 1.23 | 4.00 | 1.04 | 1.06 |
| baseline36 | | 0.54 | 1.63 | 1.46 | 1.71 | 1.46 | 0.68 | 0.74 | 1.46 | 1.46 | 1.05 |
| baseline36p3 | 1.73 | 0.64 | 0.64 | 1.91 | 1.38 | 1.91 | 0.59 | 1.36 | 1.91 | 1.11 | 1.03 |
| baseline36p5 | 1.09 | 0.78 | 0.75 | 2.56 | 1.30 | 2.56 | 0.37 | 1.22 | 2.60 | 1.00 | 1.02 |
| baseline37 | | 0.54 | 1.66 | 1.46 | 1.71 | 1.46 | 0.77 | 0.74 | 1.46 | 1.46 | 1.06 |
| baseline37p3 | 1.72 | 0.60 | 0.64 | 1.91 | 1.39 | 1.91 | 0.58 | 1.39 | 1.91 | 1.11 | 1.03 |
| baseline37p5 | 1.13 | 0.63 | 0.76 | 2.56 | 1.28 | 2.56 | 0.42 | 1.16 | 2.60 | 1.00 | 1.01 |
| baseline38 | | 0.54 | 1.65 | 1.46 | 1.72 | 1.46 | 0.72 | 0.75 | 1.46 | 1.46 | 1.07 |
| baseline38p3 | 1.66 | 0.50 | 0.64 | 1.91 | 1.38 | 1.91 | 0.55 | 1.39 | 1.91 | 1.11 | 1.02 |
| baseline38p5 | 1.11 | 0.60 | 0.76 | 2.56 | 1.29 | 2.56 | 0.38 | 1.21 | 2.60 | 1.00 | 1.02 |
| baseline39 | | 0.54 | 1.64 | 1.46 | 1.71 | 1.46 | 0.71 | 0.74 | 1.46 | 1.46 | 1.06 |
| baseline39p3 | 1.47 | 0.51 | 0.64 | 1.91 | 1.38 | 1.91 | 0.58 | 1.16 | 1.91 | 1.11 | 1.02 |
| baseline39p5 | 1.03 | 0.55 | 0.76 | 2.56 | 1.31 | 2.56 | 0.39 | 1.07 | 2.60 | 1.00 | 1.01 |
| baseline40 | | 0.97 | 1.65 | 1.47 | 1.72 | 1.47 | 0.68 | 0.73 | 1.41 | 1.41 | 1.06 |
| baseline40p3 | 1.58 | 0.51 | 1.25 | 1.85 | 1.42 | 1.85 | 0.58 | 1.16 | 1.85 | 1.11 | 1.06 |
| baseline40p5 | 1.08 | 0.56 | 1.03 | 3.06 | 1.25 | 3.06 | 0.32 | 1.05 | 3.19 | 1.01 | 1.00 |
| baseline41 | | 0.98 | 1.67 | 1.27 | 1.72 | 1.27 | 0.79 | 0.74 | 1.39 | 1.39 | 1.05 |
| baseline41p3 | 0.82 | 0.72 | 1.21 | 1.42 | 1.12 | 1.42 | 0.45 | 1.11 | 1.42 | 1.01 | 0.85 |
| baseline41p5 | 0.96 | 0.50 | 0.89 | 3.36 | 1.07 | 3.36 | 0.46 | 1.02 | 3.45 | 0.97 | 0.90 |
| baseline43 | | 0.98 | 1.40 | 1.28 | 1.69 | 1.28 | 0.77 | 0.76 | 1.21 | 1.21 | 1.02 |

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**Table 5 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline43p3 | 1.04 | 0.60 | 1.03 | 2.38 | 1.31 | 2.38 | 0.52 | 1.10 | 2.38 | 0.99 | 0.95 |
| baseline43p5 | 1.12 | 0.47 | 1.03 | 2.79 | 1.29 | 2.79 | 0.44 | 1.09 | 2.81 | 0.97 | 0.99 |
| baseline44 | | 1.00 | 1.41 | 1.32 | 1.59 | 1.32 | 0.76 | 0.75 | 1.17 | 1.17 | 1.01 |
| baseline44p3 | 1.12 | 0.58 | 0.96 | 2.46 | 1.47 | 2.46 | 0.53 | 1.10 | 2.46 | 1.00 | 0.95 |
| baseline44p5 | 1.08 | 0.47 | 0.93 | 2.42 | 1.34 | 2.42 | 0.48 | 1.08 | 2.45 | 0.99 | 0.96 |
| baseline45 | | 0.98 | 1.36 | 1.54 | 1.58 | 1.54 | 0.82 | 0.75 | 1.16 | 1.16 | 0.94 |
| baseline45p3 | 1.04 | 0.59 | 1.31 | 1.74 | 1.40 | 1.74 | 0.45 | 1.22 | 1.74 | 0.91 | 1.03 |
| baseline45p5 | 1.00 | 0.53 | 1.30 | 2.51 | 1.35 | 2.51 | 0.45 | 1.19 | 2.55 | 0.95 | 1.01 |
| baseline46 | | 0.96 | 1.36 | 1.54 | 1.57 | 1.54 | 0.76 | 0.74 | 1.15 | 1.15 | 0.90 |
| baseline46p3 | 1.11 | 0.70 | 1.17 | 1.34 | 1.22 | 1.34 | 0.46 | 1.08 | 1.34 | 0.84 | 1.04 |
| baseline46p5 | 1.01 | 0.53 | 1.12 | 2.55 | 1.29 | 2.55 | 0.46 | 1.07 | 2.59 | 0.92 | 1.03 |
| baseline47 | | 0.96 | 1.52 | 1.26 | 1.50 | 1.26 | 0.78 | 0.74 | 1.18 | 1.18 | 0.86 |
| baseline47p3 | 1.16 | 0.62 | 1.18 | 1.46 | 1.22 | 1.46 | 0.41 | 1.07 | 1.46 | 0.79 | 1.04 |
| baseline47p5 | 1.06 | 0.55 | 1.15 | 2.77 | 1.27 | 2.77 | 0.42 | 1.06 | 2.80 | 0.85 | 1.02 |
| baseline48 | | 0.99 | 1.58 | 1.22 | 1.49 | 1.22 | 0.74 | 0.74 | 1.18 | 1.18 | 0.86 |
| baseline48p3 | 1.09 | 0.62 | 1.19 | 1.59 | 1.19 | 1.59 | 0.48 | 1.10 | 1.59 | 0.79 | 1.03 |
| baseline48p5 | 1.06 | 0.55 | 1.27 | 2.73 | 1.25 | 2.73 | 0.47 | 1.06 | 2.78 | 0.84 | 1.02 |
| baseline49 | | 0.96 | 1.52 | 1.20 | 1.51 | 1.20 | 0.78 | 0.74 | 1.14 | 1.14 | 0.84 |
| baseline49p3 | 1.04 | 0.61 | 1.23 | 1.55 | 1.06 | 1.55 | 0.48 | 1.10 | 1.55 | 0.76 | 0.99 |
| baseline49p5 | 0.91 | 0.58 | 1.32 | 2.72 | 1.05 | 2.72 | 0.45 | 1.06 | 2.77 | 0.80 | 0.98 |
| baseline50 | | 0.96 | 1.46 | 1.25 | 1.50 | 1.25 | 0.75 | 0.73 | 1.15 | 1.15 | 0.84 |
| baseline50p3 | 0.90 | 0.92 | 1.16 | 1.93 | 1.06 | 1.93 | 0.54 | 1.14 | 1.93 | 0.84 | 0.96 |
| baseline50p5 | 0.84 | 0.55 | 1.16 | 2.69 | 1.14 | 2.69 | 0.49 | 1.12 | 2.75 | 0.97 | 0.97 |
| baseline51 | | 0.90 | 1.44 | 1.00 | 1.51 | 1.00 | 0.65 | 0.73 | 1.15 | 1.15 | 0.84 |
| baseline51p3 | 0.83 | 0.63 | 1.17 | 1.82 | 1.02 | 1.82 | 0.49 | 1.17 | 1.82 | 0.85 | 0.95 |
| baseline51p5 | 0.96 | 0.55 | 1.20 | 2.54 | 1.10 | 2.54 | 0.49 | 1.14 | 2.58 | 0.97 | 0.96 |
| baseline53 | | 0.82 | 1.45 | 0.92 | 1.24 | 0.93 | 0.76 | 0.74 | 1.14 | 1.14 | 0.82 |
| baseline53p3 | 0.83 | 0.64 | 0.70 | 1.56 | 0.84 | 1.56 | 0.50 | 1.05 | 1.56 | 0.84 | 0.79 |
| baseline53p5 | 0.85 | 0.52 | 0.91 | 2.37 | 0.81 | 2.37 | 0.51 | 1.05 | 2.39 | 1.02 | 0.85 |
| baseline54 | | 0.78 | 1.57 | 0.96 | 0.74 | 0.97 | 0.72 | 0.74 | 1.13 | 1.13 | 0.74 |
| baseline54p3 | 0.87 | 0.61 | 0.67 | 1.36 | 0.94 | 1.36 | 0.53 | 0.94 | 1.36 | 0.79 | 0.79 |
| baseline54p5 | 0.81 | 0.50 | 0.94 | 2.69 | 0.91 | 2.69 | 0.50 | 0.94 | 2.70 | 1.04 | 0.86 |
| baseline55 | | 0.89 | 1.72 | 0.96 | 0.76 | 0.97 | 0.73 | 0.74 | 1.13 | 1.13 | 0.74 |
| baseline55p3 | 0.81 | 0.61 | 0.71 | 1.44 | 0.94 | 1.44 | 0.54 | 0.94 | 1.44 | 0.79 | 0.79 |
| baseline55p5 | 0.79 | 1.07 | 1.05 | 2.50 | 0.88 | 2.50 | 0.60 | 0.94 | 2.50 | 0.97 | 0.84 |
| baseline56 | | 0.70 | 1.72 | 1.05 | 0.74 | 1.05 | 0.75 | 0.74 | 1.13 | 1.13 | 0.74 |
| baseline56p3 | 0.80 | 0.63 | 1.03 | 1.02 | 1.06 | 1.02 | 0.57 | 0.91 | 1.02 | 0.80 | 0.79 |
| baseline56p5 | 0.81 | 0.53 | 0.98 | 2.30 | 0.91 | 2.30 | 0.61 | 0.93 | 2.30 | 0.92 | 0.82 |
| baseline57 | | 0.70 | 1.66 | 1.05 | 0.76 | 1.05 | 0.79 | 0.74 | 1.13 | 1.13 | 0.73 |
| baseline57p3 | 0.81 | 0.63 | 1.04 | 1.02 | 1.05 | 1.02 | 0.57 | 0.91 | 1.02 | 0.80 | 0.79 |
| baseline57p5 | 0.81 | 0.52 | 0.98 | 2.30 | 0.91 | 2.30 | 0.58 | 0.93 | 2.30 | 0.92 | 0.82 |
| baseline58 | | 0.70 | 1.62 | 1.05 | 0.74 | 1.05 | 0.71 | 0.74 | 1.13 | 1.13 | 0.74 |
| baseline58p3 | 0.84 | 0.63 | 1.04 | 1.02 | 1.04 | 1.02 | 0.55 | 0.91 | 1.02 | 0.80 | 0.79 |
| baseline58p5 | 0.77 | 0.52 | 0.98 | 2.30 | 0.92 | 2.30 | 0.66 | 0.93 | 2.30 | 0.92 | 0.82 |
| baseline85 | | 0.51 | 1.58 | 1.22 | 0.70 | 1.22 | 0.65 | 0.76 | 1.14 | 1.14 | 0.70 |
| baseline85p3 | 0.63 | 0.53 | 1.04 | 1.18 | 0.83 | 1.18 | 0.63 | 0.89 | 1.18 | 0.89 | 0.84 |
| baseline85p5 | 0.72 | 0.52 | 0.89 | 1.14 | 0.79 | 1.14 | 0.53 | 0.93 | 1.14 | 1.10 | 0.88 |
| baseline87 | | 0.52 | 1.58 | 1.14 | 0.69 | 1.14 | 0.71 | 0.75 | 1.14 | 1.14 | 0.72 |
| baseline87p3 | 0.64 | 0.54 | 1.04 | 1.18 | 0.77 | 1.18 | 0.62 | 0.87 | 1.18 | 0.90 | 0.83 |
| baseline87p5 | 0.72 | 0.51 | 0.99 | 1.21 | 0.92 | 1.21 | 0.61 | 0.92 | 1.21 | 0.92 | 0.86 |
| baseline90 | | 0.53 | 1.57 | 1.15 | 0.68 | 1.15 | 0.77 | 0.75 | 1.15 | 1.15 | 0.72 |
| baseline90p3 | 0.61 | 0.51 | 0.90 | 1.11 | 0.66 | 1.11 | 0.63 | 0.87 | 1.11 | 0.91 | 0.79 |
| baseline90p5 | 0.69 | 0.90 | 0.87 | 1.15 | 0.70 | 1.15 | 0.59 | 0.90 | 1.15 | 0.94 | 0.84 |
| baseline91 | | 0.52 | 1.66 | 1.14 | 0.70 | 1.14 | 0.71 | 0.74 | 1.15 | 1.15 | 0.71 |
| baseline91p3 | 0.63 | 0.52 | 0.90 | 1.13 | 0.71 | 1.13 | 0.65 | 0.88 | 1.13 | 0.91 | 0.81 |
| baseline91p5 | 0.69 | 0.93 | 0.85 | 1.19 | 0.82 | 1.19 | 0.59 | 0.90 | 1.19 | 0.99 | 0.86 |
| baseline92 | | 0.51 | 1.58 | 1.17 | 0.67 | 1.17 | 0.70 | 0.75 | 1.15 | 1.15 | 0.71 |
| baseline92p3 | 0.62 | 0.52 | 0.67 | 1.21 | 0.68 | 1.21 | 0.65 | 0.85 | 1.21 | 0.93 | 0.80 |
| baseline92p5 | 0.69 | 0.85 | 0.85 | 1.27 | 0.82 | 1.27 | 0.59 | 0.88 | 1.27 | 1.07 | 0.86 |

**Source:** Own elaboration.

**Notes:** Each specification name encodes four attributes. The prefix indicates the flattening approach: *baseline* uses baseline flattening (three lags); *expanded* applies extended flattening (four or five lags). *baseline** shares the same baseline flattening as *baseline* but is used as a prefix to easily identify the best-performing variable grouping from the pre-selection exercise. The number following the prefix (e.g., 35, 40, 52) identifies the variable grouping. Suffixes *p3* and *p5* indicate PCA retaining 3 or 5 components; *l2* denotes two autoregressive lags of GDP; the absence of these suffixes indicates no dimensionality reduction and no autoregressive lags. *human1* refers to a judgment-based specification constructed by the authors and does not follow this naming convention. See Section 3.2 for a full description of specifications.

Table 6: RMSE across specifications and models (vintage $p = 0$)

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline*52 | | 0.64 | 1.49 | 1.76 | 1.18 | 1.76 | 0.75 | 0.75 | 5.43 | 5.43 | 0.78 |
| baseline*52p3 | 0.55 | 0.45 | 0.94 | 2.57 | 0.93 | 2.57 | 0.53 | 0.96 | 2.57 | 1.01 | 0.78 |
| baseline*52p5 | 0.49 | 0.38 | 0.90 | 1.80 | 1.10 | 1.80 | 0.51 | 0.96 | 1.80 | 0.99 | 0.84 |
| baseline*52p5l2 | | 0.37 | | | | | | 0.96 | | | |
| expanded35 | | | 1.57 | 10.33 | 1.36 | 10.10 | 0.70 | | 4.18 | 4.18 | 0.77 |
| expanded35p3 | | | 1.21 | 1.66 | 0.75 | 0.80 | 0.72 | | 1.66 | 1.51 | 0.62 |
| expanded35p5 | | | 1.10 | 2.33 | 0.63 | 3.28 | 0.55 | | 4.07 | 0.82 | 0.66 |
| expanded35p5l2 | | 0.42 | 1.10 | 2.33 | 0.65 | 3.28 | 0.54 | 1.19 | 4.07 | 0.82 | 0.66 |
| expanded36 | | | 1.58 | 10.10 | 1.37 | 9.46 | 0.69 | | 4.15 | 4.15 | 0.84 |
| expanded36p3 | | | 1.22 | 1.82 | 0.79 | 1.02 | 0.74 | | 1.82 | 1.59 | 0.64 |
| expanded36p5 | | | 1.12 | 4.04 | 0.76 | 3.52 | 0.34 | | 5.13 | 0.79 | 0.64 |
| expanded36p5l2 | | 0.42 | 1.12 | 4.04 | 0.77 | 3.52 | 0.36 | 1.18 | 5.13 | 0.79 | 0.65 |
| expanded37 | | | 1.58 | 10.10 | 1.38 | 9.46 | 0.72 | | 4.15 | 4.15 | 0.83 |
| expanded37p3 | | | 1.22 | 1.82 | 0.79 | 1.02 | 0.75 | | 1.82 | 1.59 | 0.64 |
| expanded37p5 | | | 1.12 | 4.04 | 0.78 | 3.52 | 0.32 | | 5.13 | 0.79 | 0.65 |
| expanded37p5l2 | | 0.42 | 1.12 | 4.04 | 0.80 | 3.52 | 0.39 | 1.13 | 5.13 | 0.79 | 0.65 |
| expanded38 | | | 1.57 | 10.10 | 1.37 | 9.46 | 0.72 | | 4.15 | 4.15 | 0.83 |
| expanded38p3 | | | 1.22 | 1.82 | 0.81 | 1.02 | 0.76 | | 1.82 | 1.59 | 0.63 |
| expanded38p5 | | | 1.11 | 4.04 | 0.79 | 3.52 | 0.34 | | 5.13 | 0.79 | 0.66 |
| expanded38p5l2 | | 0.43 | 1.12 | 4.04 | 0.78 | 3.52 | 0.34 | 1.18 | 5.13 | 0.79 | 0.65 |
| expanded39 | | | 1.59 | 10.10 | 1.39 | 9.46 | 0.71 | | 4.15 | 4.15 | 0.83 |
| expanded39p3 | | | 1.22 | 1.82 | 0.78 | 1.02 | 0.82 | | 1.82 | 1.59 | 0.63 |
| expanded39p5 | | | 1.11 | 4.04 | 0.76 | 3.52 | 0.34 | | 5.13 | 0.79 | 0.65 |
| expanded39p5l2 | | 0.63 | 1.12 | 4.04 | 0.76 | 3.52 | 0.35 | 1.04 | 5.13 | 0.79 | 0.64 |
| expanded40 | | | 1.56 | 8.96 | 1.39 | 8.51 | 0.72 | | 4.05 | 4.05 | 0.83 |
| expanded40p3 | | | 1.17 | 1.90 | 0.75 | 1.18 | 0.77 | | 1.90 | 1.71 | 0.67 |
| expanded40p5 | | | 1.14 | 2.67 | 0.68 | 2.91 | 0.64 | | 2.90 | 1.25 | 0.79 |
| expanded40p5l2 | | 0.53 | 1.14 | 2.67 | 0.68 | 2.91 | 0.60 | 1.02 | 2.90 | 1.25 | 0.79 |
| expanded41 | | | 1.57 | 8.28 | 1.39 | 8.03 | 0.80 | | 4.10 | 4.10 | 0.82 |
| expanded41p3 | | | 1.23 | 2.47 | 1.60 | 2.57 | 1.03 | | 2.47 | 1.87 | 1.13 |
| expanded41p5 | | | 1.03 | 2.90 | 1.36 | 3.61 | 1.22 | | 3.37 | 1.99 | 1.14 |
| expanded41p5l2 | | 0.39 | 1.03 | 2.90 | 1.38 | 3.61 | 1.23 | 0.98 | 3.37 | 1.99 | 1.14 |
| expanded43 | | | 1.46 | 5.48 | 1.35 | 5.53 | 0.71 | | 2.81 | 2.81 | 0.78 |
| expanded43p3 | | | 1.00 | 2.05 | 1.21 | 1.76 | 0.51 | | 2.05 | 0.93 | 0.70 |
| expanded43p5 | | | 0.93 | 2.53 | 1.34 | 3.50 | 0.53 | | 2.59 | 1.19 | 0.81 |
| expanded43p5l2 | | 0.39 | 0.93 | 2.53 | 1.34 | 3.50 | 0.51 | 1.04 | 2.59 | 1.19 | 0.81 |
| expanded44 | | | 1.46 | 4.94 | 1.32 | 5.11 | 0.68 | | 3.17 | 3.17 | 0.78 |
| expanded44p3 | | | 0.95 | 2.52 | 1.25 | 2.01 | 0.54 | | 2.52 | 1.04 | 0.73 |
| expanded44p5 | | | 1.14 | 1.84 | 1.25 | 1.20 | 0.48 | | 1.94 | 1.23 | 0.76 |
| expanded44p5l2 | | 0.39 | 1.10 | 1.84 | 1.28 | 1.20 | 0.50 | 1.03 | 1.94 | 1.23 | 0.76 |
| expanded45 | | | 1.47 | 3.74 | 1.31 | 3.90 | 0.67 | | 3.14 | 3.14 | 0.76 |
| expanded45p3 | | | 1.40 | 2.16 | 1.02 | 1.61 | 0.47 | | 2.16 | 0.85 | 0.87 |
| expanded45p5 | | | 1.01 | 2.53 | 1.20 | 2.36 | 0.49 | | 2.41 | 0.72 | 0.89 |
| expanded45p5l2 | | 0.39 | 1.01 | 2.53 | 1.20 | 2.36 | 0.50 | 1.12 | 2.41 | 0.72 | 0.89 |
| expanded46 | | | 1.46 | 3.70 | 1.31 | 3.85 | 0.65 | | 3.12 | 3.12 | 0.74 |
| expanded46p3 | | | 1.48 | 1.82 | 1.25 | 1.25 | 0.46 | | 1.82 | 0.76 | 0.89 |
| expanded46p5 | | | 1.12 | 2.82 | 1.41 | 3.13 | 0.41 | | 2.73 | 0.68 | 0.90 |
| expanded46p5l2 | | 0.39 | 1.12 | 2.82 | 1.42 | 3.13 | 0.42 | 1.04 | 2.73 | 0.68 | 0.90 |
| expanded47 | | | 1.78 | 4.05 | 1.25 | 4.60 | 0.76 | | 3.05 | 3.05 | 0.74 |
| expanded47p3 | | | 1.32 | 1.79 | 1.21 | 1.14 | 0.47 | | 1.79 | 0.71 | 0.88 |
| expanded47p5 | | | 1.12 | 2.74 | 1.36 | 1.72 | 0.42 | | 2.72 | 0.72 | 0.90 |
| expanded47p5l2 | | 0.38 | 1.08 | 2.74 | 1.36 | 1.72 | 0.43 | 1.03 | 2.72 | 0.72 | 0.90 |
| expanded48 | | | 1.83 | 3.32 | 1.22 | 3.82 | 0.84 | | 3.06 | 3.06 | 0.74 |
| expanded48p3 | | | 1.07 | 1.75 | 1.28 | 1.31 | 0.52 | | 1.75 | 0.76 | 0.95 |
| expanded48p5 | | | 1.07 | 2.46 | 1.37 | 1.68 | 0.45 | | 2.59 | 0.78 | 0.98 |
| expanded48p5l2 | | 0.38 | 1.08 | 2.46 | 1.39 | 1.68 | 0.45 | 1.03 | 2.59 | 0.78 | 0.99 |
| expanded49 | | | 1.65 | 2.74 | 1.28 | 3.33 | 0.70 | | 3.08 | 3.08 | 0.71 |
| expanded49p3 | | | 1.03 | 1.52 | 1.06 | 1.40 | 0.51 | | 1.52 | 0.80 | 0.84 |
| expanded49p5 | | | 1.17 | 2.39 | 1.24 | 1.35 | 0.44 | | 2.48 | 0.74 | 0.93 |
| expanded49p5l2 | | 0.39 | 1.17 | 2.39 | 1.27 | 1.35 | 0.44 | 1.02 | 2.48 | 0.74 | 0.93 |
| expanded50 | | | 1.70 | 1.88 | 1.27 | 2.39 | 0.70 | | 3.04 | 3.04 | 0.71 |
| expanded50p3 | | | 0.61 | 1.53 | 1.02 | 1.54 | 0.57 | | 1.53 | 0.80 | 0.82 |
| expanded50p5 | | | 0.76 | 1.70 | 1.15 | 1.03 | 0.52 | | 1.63 | 0.90 | 0.91 |
| expanded50p5l2 | | 0.39 | 0.76 | 1.70 | 1.14 | 1.03 | 0.47 | 1.06 | 1.63 | 0.90 | 0.90 |
| expanded51 | | | 1.65 | 2.83 | 1.28 | 3.49 | 0.71 | | 3.02 | 3.02 | 0.75 |
| expanded51p3 | | | 0.67 | 1.62 | 1.06 | 1.59 | 0.58 | | 1.62 | 0.82 | 0.81 |
| expanded51p5 | | | 0.91 | 2.41 | 1.16 | 1.13 | 0.52 | | 2.54 | 0.91 | 0.91 |
| expanded51p5l2 | | 0.62 | 0.91 | 2.41 | 1.16 | 1.13 | 0.50 | 1.08 | 2.54 | 0.91 | 0.91 |
| expanded52 | | | 1.55 | 1.48 | 1.08 | 2.08 | 0.70 | | 2.99 | 2.99 | 0.71 |

Continued on next page

Table 6 – continued

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| expanded52p3 | | | 0.66 | 1.91 | 0.72 | 1.95 | 0.54 | | 1.91 | 0.83 | 0.69 |
| expanded52p5 | | | 0.66 | 2.23 | 0.87 | 0.95 | 0.51 | | 2.38 | 0.84 | 0.77 |
| expanded52p5l2 | | | 0.66 | 2.23 | 0.85 | 0.95 | 0.50 | | 2.38 | 0.84 | 0.78 |
| expanded53 | | | 1.50 | 1.95 | 1.07 | 2.51 | 0.75 | | 2.99 | 2.99 | 0.71 |
| expanded53p3 | | | 1.07 | 2.07 | 0.89 | 2.31 | 0.53 | | 2.07 | 1.69 | 0.73 |
| expanded53p5 | | | 0.68 | 2.10 | 1.08 | 1.26 | 0.48 | | 2.11 | 1.14 | 0.85 |
| expanded53p5l2 | | 0.38 | 0.67 | 2.10 | 1.08 | 1.26 | 0.52 | 0.98 | 2.11 | 1.14 | 0.86 |
| expanded54 | | | 1.21 | 2.08 | 0.58 | 2.72 | 0.71 | | 2.97 | 2.97 | 0.65 |
| expanded54p3 | | | 1.06 | 1.91 | 0.92 | 2.00 | 0.62 | | 1.91 | 1.61 | 0.72 |
| expanded54p5 | | | 0.84 | 1.98 | 1.00 | 1.20 | 0.51 | | 1.93 | 1.10 | 0.83 |
| expanded54p5l2 | | 0.61 | 0.84 | 1.98 | 0.94 | 1.20 | 0.47 | 0.85 | 1.93 | 1.10 | 0.81 |
| expanded55 | | | 1.35 | 2.70 | 0.59 | 3.24 | 0.72 | | 2.95 | 2.95 | 0.65 |
| expanded55p3 | | | 1.08 | 1.95 | 0.87 | 2.16 | 0.61 | | 1.95 | 0.88 | 0.77 |
| expanded55p5 | | | 0.80 | 2.01 | 0.96 | 1.74 | 0.56 | | 2.00 | 1.02 | 0.84 |
| expanded55p5l2 | | 0.61 | 0.79 | 2.01 | 0.97 | 1.74 | 0.58 | 0.85 | 2.00 | 1.02 | 0.84 |
| expanded56 | | | 1.30 | 2.78 | 0.58 | 3.30 | 0.65 | | 2.95 | 2.95 | 0.65 |
| expanded56p3 | | | 0.81 | 1.97 | 0.87 | 2.04 | 0.59 | | 1.97 | 0.87 | 0.68 |
| expanded56p5 | | | 0.99 | 1.98 | 0.67 | 0.90 | 0.57 | | 1.99 | 1.84 | 0.75 |
| expanded56p5l2 | | 0.38 | 0.99 | 1.98 | 0.64 | 0.90 | 0.59 | 0.84 | 1.99 | 1.84 | 0.76 |
| expanded57 | | | 1.24 | 2.78 | 0.57 | 3.30 | 0.78 | | 2.95 | 2.95 | 0.65 |
| expanded57p3 | | | 0.82 | 1.97 | 0.90 | 2.04 | 0.57 | | 1.97 | 0.87 | 0.68 |
| expanded57p5 | | | 0.98 | 1.98 | 0.64 | 0.90 | 0.59 | | 1.99 | 1.84 | 0.76 |
| expanded57p5l2 | | 0.38 | 0.99 | 1.98 | 0.65 | 0.90 | 0.59 | 0.84 | 1.99 | 1.84 | 0.76 |
| expanded58 | | | 1.34 | 2.78 | 0.57 | 3.30 | 0.78 | | 2.95 | 2.95 | 0.64 |
| expanded58p3 | | | 0.83 | 1.97 | 0.93 | 2.04 | 0.58 | | 1.97 | 0.87 | 0.68 |
| expanded58p5 | | | 0.98 | 1.98 | 0.63 | 0.90 | 0.57 | | 1.99 | 1.84 | 0.75 |
| expanded58p5l2 | | 0.60 | 0.99 | 1.98 | 0.64 | 0.90 | 0.58 | 0.84 | 1.99 | 1.84 | 0.76 |
| expanded85 | | | 1.19 | 1.26 | 0.53 | 1.21 | 0.68 | | 2.30 | 2.29 | 0.62 |
| expanded85p3 | | | 0.99 | 1.70 | 0.87 | 1.49 | 0.60 | | 1.80 | 0.93 | 0.84 |
| expanded85p5 | | | 0.88 | 0.95 | 0.85 | 0.72 | 0.60 | | 0.95 | 0.95 | 0.83 |
| expanded85p5l2 | | 0.40 | 0.88 | 0.95 | 0.87 | 0.72 | 0.53 | 0.93 | 0.95 | 0.95 | 0.83 |
| expanded87 | | | 1.24 | 0.65 | 0.51 | 0.64 | 0.72 | | 2.29 | 2.29 | 0.62 |
| expanded87p3 | | | 0.94 | 1.34 | 0.86 | 1.08 | 0.57 | | 1.43 | 1.00 | 0.85 |
| expanded87p5 | | | 0.98 | 1.09 | 0.87 | 0.82 | 0.53 | | 1.17 | 1.08 | 0.80 |
| expanded87p5l2 | | 0.40 | 0.98 | 1.09 | 0.88 | 0.82 | 0.56 | 0.92 | 1.17 | 1.08 | 0.80 |
| expanded90 | | | 1.29 | 0.77 | 0.52 | 0.74 | 0.72 | | 2.27 | 2.27 | 0.61 |
| expanded90p3 | | | 1.01 | 1.11 | 0.83 | 0.97 | 0.63 | | 1.13 | 0.95 | 0.86 |
| expanded90p5 | | | 1.07 | 1.03 | 0.75 | 1.07 | 0.55 | | 1.06 | 0.93 | 0.78 |
| expanded90p5l2 | | 0.54 | 1.08 | 1.03 | 0.76 | 1.07 | 0.55 | 0.90 | 1.06 | 0.93 | 0.78 |
| expanded91 | | | 1.20 | 0.81 | 0.49 | 0.79 | 0.76 | | 2.27 | 2.27 | 0.62 |
| expanded91p3 | | | 1.02 | 1.11 | 0.84 | 0.97 | 0.61 | | 1.12 | 0.96 | 0.86 |
| expanded91p5 | | | 1.02 | 1.07 | 0.86 | 0.88 | 0.60 | | 1.09 | 0.66 | 0.81 |
| expanded91p5l2 | | 0.56 | 1.02 | 1.07 | 0.87 | 0.88 | 0.59 | 0.90 | 1.09 | 0.66 | 0.81 |
| expanded92 | | | 1.20 | 0.83 | 0.47 | 0.81 | 0.71 | | 2.26 | 2.26 | 0.60 |
| expanded92p3 | | | 1.00 | 1.03 | 0.76 | 0.96 | 0.57 | | 1.05 | 0.97 | 0.82 |
| expanded92p5 | | | 1.05 | 1.12 | 0.80 | 0.88 | 0.55 | | 1.15 | 0.66 | 0.78 |
| expanded92p5l2 | | 0.52 | 1.04 | 1.12 | 0.80 | 0.88 | 0.56 | 0.88 | 1.15 | 0.66 | 0.79 |
| human1 | 0.54 | 0.39 | 0.89 | 1.90 | 0.75 | 2.10 | 0.51 | | 0.95 | 1.02 | 0.71 |
| baseline35 | | 0.35 | 1.38 | 13.90 | 1.44 | 13.90 | 0.66 | 0.78 | 9.58 | 9.57 | 0.89 |
| baseline35p3 | 1.05 | 0.43 | 1.24 | 2.95 | 0.94 | 2.95 | 0.69 | 1.31 | 2.95 | 1.54 | 0.63 |
| baseline35p5 | 0.69 | 0.43 | 1.23 | 2.35 | 0.83 | 2.35 | 0.55 | 1.19 | 2.83 | 1.17 | 0.71 |
| baseline36 | | 0.34 | 1.39 | 13.50 | 1.47 | 13.50 | 0.64 | 0.77 | 9.24 | 9.24 | 0.93 |
| baseline36p3 | 1.04 | 0.43 | 1.24 | 3.16 | 1.00 | 3.16 | 0.79 | 1.33 | 3.16 | 1.57 | 0.64 |
| baseline36p5 | 0.74 | 0.49 | 1.32 | 2.24 | 0.94 | 2.24 | 0.35 | 1.18 | 2.27 | 1.11 | 0.73 |
| baseline37 | | 0.34 | 1.40 | 13.50 | 1.46 | 13.50 | 0.72 | 0.74 | 9.24 | 9.24 | 0.93 |
| baseline37p3 | 1.08 | 0.43 | 1.24 | 3.16 | 1.00 | 3.16 | 0.76 | 1.35 | 3.16 | 1.57 | 0.64 |
| baseline37p5 | 0.76 | 0.42 | 1.32 | 2.24 | 0.89 | 2.24 | 0.39 | 1.13 | 2.27 | 1.11 | 0.72 |
| baseline38 | | 0.34 | 1.38 | 13.50 | 1.47 | 13.50 | 0.70 | 0.77 | 9.24 | 9.24 | 0.95 |
| baseline38p3 | 1.02 | 0.39 | 1.24 | 3.16 | 0.97 | 3.16 | 0.73 | 1.35 | 3.16 | 1.57 | 0.64 |
| baseline38p5 | 0.66 | 0.41 | 1.32 | 2.24 | 0.90 | 2.24 | 0.36 | 1.18 | 2.27 | 1.11 | 0.74 |
| baseline39 | | 0.34 | 1.40 | 13.50 | 1.47 | 13.50 | 0.70 | 0.73 | 9.24 | 9.24 | 0.95 |
| baseline39p3 | 0.94 | 0.40 | 1.24 | 3.16 | 1.00 | 3.16 | 0.75 | 1.12 | 3.16 | 1.57 | 0.64 |
| baseline39p5 | 0.62 | 0.41 | 1.32 | 2.24 | 0.92 | 2.24 | 0.36 | 1.04 | 2.27 | 1.11 | 0.73 |
| baseline40 | | 0.75 | 1.39 | 12.75 | 1.47 | 12.75 | 0.65 | 0.71 | 9.51 | 9.50 | 0.94 |
| baseline40p3 | 0.99 | 0.40 | 1.27 | 3.25 | 1.05 | 3.25 | 0.74 | 1.12 | 3.25 | 1.61 | 0.68 |
| baseline40p5 | 0.67 | 0.41 | 1.26 | 2.28 | 0.92 | 2.28 | 0.60 | 1.02 | 2.28 | 1.63 | 0.81 |
| baseline41 | | 0.75 | 1.38 | 12.76 | 1.47 | 12.76 | 0.78 | 0.71 | 9.48 | 9.47 | 0.94 |
| baseline41p3 | 0.54 | 0.50 | 1.45 | 2.56 | 1.57 | 2.56 | 1.04 | 1.05 | 2.56 | 1.87 | 1.14 |
| baseline41p5 | 0.67 | 0.39 | 1.12 | 2.74 | 1.46 | 2.74 | 1.20 | 0.98 | 2.73 | 2.08 | 1.10 |
| baseline43 | | 0.73 | 1.30 | 7.90 | 1.44 | 7.90 | 0.75 | 0.77 | 5.04 | 5.04 | 0.91 |

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**Table 6 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline43p3 | 0.72 | 0.45 | 1.02 | 3.33 | 1.34 | 3.33 | 0.53 | 1.05 | 3.33 | 1.26 | 0.80 |
| baseline43p5 | 0.75 | 0.39 | 1.02 | 3.07 | 1.25 | 3.07 | 0.55 | 1.04 | 3.08 | 1.24 | 0.84 |
| baseline44 | | 0.63 | 1.30 | 7.01 | 1.37 | 7.01 | 0.75 | 0.76 | 5.66 | 5.66 | 0.91 |
| baseline44p3 | 0.81 | 0.45 | 0.96 | 3.47 | 1.47 | 3.47 | 0.52 | 1.04 | 3.47 | 1.28 | 0.84 |
| baseline44p5 | 0.74 | 0.39 | 0.95 | 2.97 | 1.30 | 2.98 | 0.52 | 1.03 | 2.99 | 1.12 | 0.81 |
| baseline45 | | 0.73 | 1.28 | 5.51 | 1.38 | 5.51 | 0.73 | 0.80 | 5.67 | 5.66 | 0.86 |
| baseline45p3 | 0.78 | 0.43 | 1.37 | 2.92 | 1.26 | 2.92 | 0.47 | 1.15 | 2.92 | 1.15 | 0.99 |
| baseline45p5 | 0.74 | 0.39 | 1.42 | 2.92 | 1.42 | 2.92 | 0.46 | 1.12 | 2.94 | 1.05 | 0.98 |
| baseline46 | | 0.73 | 1.30 | 5.41 | 1.37 | 5.41 | 0.75 | 0.73 | 5.67 | 5.66 | 0.84 |
| baseline46p3 | 0.75 | 0.46 | 1.36 | 2.38 | 1.32 | 2.38 | 0.49 | 1.04 | 2.38 | 1.02 | 0.96 |
| baseline46p5 | 0.75 | 0.39 | 1.31 | 2.65 | 1.52 | 2.65 | 0.39 | 1.04 | 2.68 | 0.99 | 0.97 |
| baseline47 | | 0.73 | 1.54 | 5.85 | 1.30 | 5.86 | 0.79 | 0.73 | 5.61 | 5.60 | 0.81 |
| baseline47p3 | 0.78 | 0.43 | 1.34 | 2.47 | 1.26 | 2.47 | 0.47 | 1.03 | 2.47 | 0.96 | 0.95 |
| baseline47p5 | 0.71 | 0.39 | 1.33 | 2.88 | 1.40 | 2.88 | 0.41 | 1.03 | 2.90 | 0.92 | 0.93 |
| baseline48 | | 0.62 | 1.54 | 4.06 | 1.29 | 4.06 | 0.73 | 0.74 | 5.61 | 5.61 | 0.80 |
| baseline48p3 | 0.68 | 0.42 | 1.29 | 2.53 | 1.29 | 2.53 | 0.53 | 1.06 | 2.53 | 0.95 | 1.00 |
| baseline48p5 | 0.70 | 0.39 | 1.26 | 2.64 | 1.44 | 2.64 | 0.46 | 1.03 | 2.66 | 0.95 | 1.01 |
| baseline49 | | 0.70 | 1.51 | 3.65 | 1.31 | 3.65 | 0.79 | 0.74 | 5.50 | 5.50 | 0.79 |
| baseline49p3 | 0.67 | 0.42 | 1.10 | 2.50 | 1.14 | 2.50 | 0.52 | 1.06 | 2.50 | 0.90 | 0.91 |
| baseline49p5 | 0.58 | 0.40 | 1.22 | 2.69 | 1.29 | 2.69 | 0.41 | 1.02 | 2.71 | 0.91 | 0.94 |
| baseline50 | | 0.70 | 1.44 | 2.62 | 1.31 | 2.62 | 0.70 | 0.80 | 5.40 | 5.40 | 0.79 |
| baseline50p3 | 0.57 | 0.52 | 1.12 | 2.58 | 1.09 | 2.58 | 0.60 | 1.08 | 2.58 | 0.99 | 0.96 |
| baseline50p5 | 0.60 | 0.39 | 1.11 | 2.51 | 1.34 | 2.51 | 0.47 | 1.06 | 2.52 | 1.14 | 0.98 |
| baseline51 | | 0.69 | 1.41 | 3.47 | 1.36 | 3.47 | 0.64 | 0.82 | 5.52 | 5.52 | 0.82 |
| baseline51p3 | 0.58 | 0.44 | 1.13 | 2.58 | 1.03 | 2.58 | 0.55 | 1.10 | 2.58 | 1.01 | 0.96 |
| baseline51p5 | 0.56 | 0.39 | 1.17 | 2.51 | 1.30 | 2.51 | 0.51 | 1.08 | 2.51 | 1.12 | 0.99 |
| baseline53 | | 0.66 | 1.44 | 2.28 | 1.17 | 2.52 | 0.74 | 0.76 | 5.44 | 5.44 | 0.78 |
| baseline53p3 | 0.60 | 0.45 | 1.07 | 2.75 | 1.01 | 2.75 | 0.52 | 0.96 | 2.75 | 1.09 | 0.73 |
| baseline53p5 | 0.50 | 0.38 | 1.15 | 2.85 | 1.16 | 2.85 | 0.49 | 0.98 | 2.86 | 1.31 | 0.80 |
| baseline54 | | 0.63 | 1.31 | 2.44 | 0.58 | 2.69 | 0.73 | 0.70 | 5.39 | 5.39 | 0.69 |
| baseline54p3 | 0.49 | 0.44 | 1.14 | 2.25 | 1.10 | 2.25 | 0.61 | 0.83 | 2.25 | 0.98 | 0.83 |
| baseline54p5 | 0.52 | 0.38 | 1.29 | 2.66 | 1.25 | 2.66 | 0.46 | 0.85 | 2.67 | 1.23 | 0.88 |
| baseline55 | | 0.54 | 1.49 | 3.09 | 0.57 | 3.33 | 0.72 | 0.70 | 5.38 | 5.38 | 0.68 |
| baseline55p3 | 0.50 | 0.45 | 1.19 | 2.59 | 0.99 | 2.59 | 0.61 | 0.83 | 2.59 | 1.00 | 0.83 |
| baseline55p5 | 0.49 | 0.61 | 1.30 | 2.57 | 1.17 | 2.57 | 0.57 | 0.85 | 2.57 | 1.06 | 0.84 |
| baseline56 | | 0.63 | 1.48 | 3.17 | 0.57 | 3.40 | 0.74 | 0.70 | 5.38 | 5.38 | 0.69 |
| baseline56p3 | 0.49 | 0.45 | 1.15 | 2.35 | 0.86 | 2.35 | 0.57 | 0.82 | 2.35 | 0.99 | 0.75 |
| baseline56p5 | 0.48 | 0.39 | 1.01 | 2.55 | 0.87 | 2.55 | 0.58 | 0.84 | 2.55 | 1.03 | 0.79 |
| baseline57 | | 0.63 | 1.41 | 3.17 | 0.58 | 3.40 | 0.77 | 0.70 | 5.38 | 5.38 | 0.68 |
| baseline57p3 | 0.52 | 0.45 | 1.15 | 2.35 | 0.86 | 2.35 | 0.58 | 0.82 | 2.35 | 0.99 | 0.75 |
| baseline57p5 | 0.51 | 0.39 | 1.01 | 2.55 | 0.86 | 2.55 | 0.55 | 0.84 | 2.55 | 1.03 | 0.80 |
| baseline58 | | 0.63 | 1.36 | 3.17 | 0.56 | 3.40 | 0.73 | 0.70 | 5.38 | 5.38 | 0.69 |
| baseline58p3 | 0.54 | 0.45 | 1.15 | 2.35 | 0.84 | 2.35 | 0.55 | 0.82 | 2.35 | 0.99 | 0.75 |
| baseline58p5 | 0.52 | 0.39 | 1.01 | 2.55 | 0.86 | 2.55 | 0.64 | 0.84 | 2.55 | 1.03 | 0.79 |
| baseline85 | | 0.42 | 1.33 | 1.32 | 0.49 | 1.34 | 0.67 | 0.72 | 4.05 | 4.05 | 0.65 |
| baseline85p3 | 0.53 | 0.39 | 0.98 | 1.34 | 0.72 | 1.34 | 0.62 | 0.89 | 1.34 | 0.92 | 0.79 |
| baseline85p5 | 0.53 | 0.40 | 0.85 | 1.14 | 0.78 | 1.14 | 0.55 | 0.93 | 1.14 | 1.15 | 0.84 |
| baseline87 | | 0.43 | 1.34 | 0.69 | 0.48 | 0.69 | 0.71 | 0.71 | 4.03 | 4.03 | 0.64 |
| baseline87p3 | 0.48 | 0.39 | 0.93 | 1.23 | 0.73 | 1.23 | 0.60 | 0.87 | 1.23 | 0.91 | 0.78 |
| baseline87p5 | 0.57 | 0.40 | 0.63 | 1.43 | 0.84 | 1.43 | 0.57 | 0.92 | 1.43 | 1.11 | 0.78 |
| baseline90 | | 0.40 | 1.32 | 0.79 | 0.47 | 0.74 | 0.75 | 0.70 | 4.03 | 4.03 | 0.64 |
| baseline90p3 | 0.48 | 0.39 | 0.89 | 1.17 | 0.71 | 1.17 | 0.60 | 0.87 | 1.17 | 0.91 | 0.75 |
| baseline90p5 | 0.56 | 0.56 | 0.88 | 1.22 | 0.70 | 1.22 | 0.58 | 0.90 | 1.22 | 0.94 | 0.73 |
| baseline91 | | 0.43 | 1.43 | 0.82 | 0.48 | 0.78 | 0.70 | 0.71 | 4.01 | 4.01 | 0.64 |
| baseline91p3 | 0.49 | 0.39 | 0.88 | 1.19 | 0.71 | 1.19 | 0.61 | 0.88 | 1.19 | 0.91 | 0.77 |
| baseline91p5 | 0.52 | 0.57 | 0.96 | 1.19 | 0.84 | 1.19 | 0.55 | 0.90 | 1.19 | 0.96 | 0.74 |
| baseline92 | | 0.42 | 1.33 | 0.84 | 0.44 | 0.81 | 0.70 | 0.68 | 3.98 | 3.98 | 0.62 |
| baseline92p3 | 0.47 | 0.39 | 0.68 | 1.22 | 0.69 | 1.22 | 0.61 | 0.85 | 1.22 | 0.91 | 0.74 |
| baseline92p5 | 0.53 | 0.54 | 0.83 | 1.21 | 0.85 | 1.21 | 0.56 | 0.88 | 1.21 | 1.00 | 0.73 |

**Source:** Own elaboration.

**Notes:** Each specification name encodes four attributes. The prefix indicates the flattening approach: *baseline* uses baseline flattening (three lags); *expanded* applies extended flattening (four or five lags). *baseline** shares the same baseline flattening as *baseline* but is used as a prefix to easily identify the best-performing variable grouping from the pre-selection exercise. The number following the prefix (e.g., 35, 40, 52) identifies the variable grouping. Suffixes *p3* and *p5* indicate PCA retaining 3 or 5 components; *l2* denotes two autoregressive lags of GDP; the absence of these suffixes indicates no dimensionality reduction and no autoregressive lags. *human1* refers to a judgment-based specification constructed by the authors and does not follow this naming convention. See Section 3.2 for a full description of specifications.

Table 7: RMSE across specifications and models (vintage $p = 1$)

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline*52 | | 0.50 | 1.40 | 2.92 | 1.06 | 2.92 | 0.75 | 0.79 | 5.11 | 5.11 | 0.73 |
| baseline*52p3 | 0.56 | 0.42 | 0.68 | 2.17 | 0.64 | 2.17 | 0.49 | 0.97 | 2.17 | 0.76 | 0.63 |
| baseline*52p5 | 0.47 | 0.36 | 0.61 | 2.05 | 0.76 | 2.05 | 0.46 | 0.88 | 2.05 | 0.92 | 0.71 |
| baseline*52p5l2 | | 0.34 | | | | | | 0.88 | | | |
| expanded35 | | | 1.38 | 11.23 | 1.21 | 10.91 | 0.73 | | 3.87 | 3.87 | 0.65 |
| expanded35p3 | | | 0.86 | 2.23 | 1.02 | 2.48 | 1.50 | | 2.23 | 1.98 | 0.93 |
| expanded35p5 | | | 0.82 | 1.63 | 1.08 | 3.03 | 1.03 | | 1.09 | 1.54 | 0.96 |
| expanded35p5l2 | | 0.42 | 0.80 | 1.63 | 1.11 | 3.03 | 0.99 | 1.25 | 1.09 | 1.54 | 0.96 |
| expanded36 | | | 1.37 | 11.05 | 1.21 | 10.31 | 0.74 | | 3.90 | 3.90 | 0.73 |
| expanded36p3 | | | 1.07 | 2.63 | 1.26 | 2.19 | 1.61 | | 2.63 | 2.41 | 1.19 |
| expanded36p5 | | | 0.96 | 4.09 | 1.40 | 3.68 | 0.88 | | 4.37 | 1.85 | 1.18 |
| expanded36p5l2 | | 0.42 | 0.96 | 4.09 | 1.43 | 3.68 | 0.88 | 1.24 | 4.37 | 1.85 | 1.18 |
| expanded37 | | | 1.39 | 11.05 | 1.23 | 10.31 | 0.74 | | 3.90 | 3.90 | 0.73 |
| expanded37p3 | | | 1.08 | 2.63 | 1.27 | 2.19 | 1.61 | | 2.63 | 2.41 | 1.20 |
| expanded37p5 | | | 0.97 | 4.09 | 1.41 | 3.68 | 0.90 | | 4.37 | 1.85 | 1.18 |
| expanded37p5l2 | | 0.42 | 0.96 | 4.09 | 1.41 | 3.68 | 0.91 | 1.15 | 4.37 | 1.85 | 1.18 |
| expanded38 | | | 1.36 | 11.05 | 1.22 | 10.31 | 0.77 | | 3.90 | 3.90 | 0.73 |
| expanded38p3 | | | 1.07 | 2.63 | 1.24 | 2.19 | 1.60 | | 2.63 | 2.41 | 1.19 |
| expanded38p5 | | | 0.96 | 4.09 | 1.41 | 3.68 | 0.86 | | 4.37 | 1.85 | 1.19 |
| expanded38p5l2 | | 0.43 | 0.96 | 4.09 | 1.42 | 3.68 | 0.91 | 1.24 | 4.37 | 1.85 | 1.19 |
| expanded39 | | | 1.39 | 11.05 | 1.25 | 10.31 | 0.73 | | 3.90 | 3.90 | 0.72 |
| expanded39p3 | | | 1.08 | 2.63 | 1.24 | 2.19 | 1.63 | | 2.63 | 2.41 | 1.19 |
| expanded39p5 | | | 0.96 | 4.09 | 1.39 | 3.68 | 0.82 | | 4.37 | 1.85 | 1.18 |
| expanded39p5l2 | | 0.61 | 0.96 | 4.09 | 1.40 | 3.68 | 0.95 | 1.08 | 4.37 | 1.85 | 1.18 |
| expanded40 | | | 1.35 | 10.10 | 1.24 | 9.55 | 0.72 | | 3.81 | 3.81 | 0.72 |
| expanded40p3 | | | 0.99 | 2.66 | 1.33 | 2.27 | 1.56 | | 2.66 | 2.59 | 1.27 |
| expanded40p5 | | | 1.04 | 4.39 | 1.71 | 4.26 | 1.38 | | 4.91 | 2.44 | 1.38 |
| expanded40p5l2 | | 0.52 | 1.04 | 4.39 | 1.70 | 4.26 | 1.41 | 1.07 | 4.91 | 2.44 | 1.37 |
| expanded41 | | | 1.37 | 9.37 | 1.23 | 9.06 | 0.80 | | 3.86 | 3.86 | 0.71 |
| expanded41p3 | | | 0.89 | 0.78 | 0.91 | 0.87 | 0.42 | | 0.78 | 0.77 | 0.69 |
| expanded41p5 | | | 0.61 | 2.17 | 0.93 | 2.83 | 0.39 | | 2.44 | 0.90 | 0.69 |
| expanded41p5l2 | | 0.39 | 0.58 | 2.17 | 0.93 | 2.83 | 0.37 | 0.95 | 2.44 | 0.90 | 0.69 |
| expanded43 | | | 1.36 | 6.46 | 1.23 | 6.26 | 0.75 | | 2.67 | 2.67 | 0.71 |
| expanded43p3 | | | 1.00 | 1.96 | 1.15 | 1.84 | 0.44 | | 1.96 | 0.77 | 0.69 |
| expanded43p5 | | | 0.94 | 2.20 | 1.29 | 3.48 | 0.35 | | 2.14 | 1.13 | 0.75 |
| expanded43p5l2 | | 0.37 | 0.93 | 2.20 | 1.26 | 3.48 | 0.36 | 0.97 | 2.14 | 1.13 | 0.75 |
| expanded44 | | | 1.37 | 5.98 | 1.25 | 5.88 | 0.72 | | 2.98 | 2.98 | 0.72 |
| expanded44p3 | | | 1.09 | 2.32 | 1.19 | 2.01 | 0.43 | | 2.32 | 0.78 | 0.70 |
| expanded44p5 | | | 1.25 | 1.48 | 1.19 | 1.33 | 0.36 | | 2.40 | 1.11 | 0.70 |
| expanded44p5l2 | | 0.37 | 1.21 | 1.48 | 1.22 | 1.33 | 0.36 | 0.96 | 2.40 | 1.11 | 0.71 |
| expanded45 | | | 1.48 | 4.51 | 1.23 | 4.51 | 0.74 | | 2.96 | 2.96 | 0.69 |
| expanded45p3 | | | 1.40 | 2.11 | 0.99 | 1.77 | 0.38 | | 2.11 | 0.75 | 0.79 |
| expanded45p5 | | | 1.01 | 2.76 | 1.14 | 2.26 | 0.37 | | 2.49 | 0.74 | 0.81 |
| expanded45p5l2 | | 0.37 | 1.01 | 2.76 | 1.13 | 2.26 | 0.36 | 1.05 | 2.49 | 0.74 | 0.81 |
| expanded46 | | | 1.49 | 4.44 | 1.24 | 4.47 | 0.69 | | 2.95 | 2.95 | 0.68 |
| expanded46p3 | | | 1.48 | 1.96 | 1.12 | 1.58 | 0.38 | | 1.96 | 0.77 | 0.78 |
| expanded46p5 | | | 1.12 | 3.55 | 1.31 | 3.03 | 0.38 | | 3.46 | 0.74 | 0.79 |
| expanded46p5l2 | | 0.37 | 1.12 | 3.55 | 1.32 | 3.03 | 0.37 | 0.99 | 3.46 | 0.74 | 0.80 |
| expanded47 | | | 1.70 | 4.63 | 1.20 | 5.18 | 0.76 | | 2.89 | 2.89 | 0.65 |
| expanded47p3 | | | 1.32 | 1.95 | 1.10 | 1.58 | 0.38 | | 1.95 | 0.75 | 0.78 |
| expanded47p5 | | | 1.12 | 3.66 | 1.28 | 1.78 | 0.37 | | 3.91 | 0.82 | 0.83 |
| expanded47p5l2 | | 0.37 | 1.08 | 3.66 | 1.27 | 1.78 | 0.38 | 0.97 | 3.91 | 0.82 | 0.83 |
| expanded48 | | | 1.73 | 4.26 | 1.15 | 4.82 | 0.84 | | 2.90 | 2.90 | 0.65 |
| expanded48p3 | | | 1.10 | 1.88 | 1.17 | 1.64 | 0.43 | | 1.88 | 0.76 | 0.87 |
| expanded48p5 | | | 1.11 | 2.95 | 1.29 | 1.66 | 0.39 | | 3.47 | 0.82 | 0.90 |
| expanded48p5l2 | | 0.37 | 1.11 | 2.95 | 1.32 | 1.66 | 0.40 | 0.97 | 3.47 | 0.82 | 0.91 |
| expanded49 | | | 1.55 | 3.81 | 1.18 | 4.44 | 0.74 | | 2.90 | 2.90 | 0.65 |
| expanded49p3 | | | 1.07 | 1.62 | 0.99 | 1.66 | 0.40 | | 1.62 | 0.81 | 0.80 |
| expanded49p5 | | | 1.20 | 2.64 | 1.16 | 1.38 | 0.39 | | 3.07 | 0.77 | 0.88 |
| expanded49p5l2 | | 0.38 | 1.20 | 2.64 | 1.18 | 1.38 | 0.39 | 0.95 | 3.07 | 0.77 | 0.88 |
| expanded50 | | | 1.64 | 2.94 | 1.19 | 3.54 | 0.70 | | 2.87 | 2.87 | 0.66 |
| expanded50p3 | | | 0.62 | 1.70 | 0.81 | 1.81 | 0.47 | | 1.71 | 0.74 | 0.74 |
| expanded50p5 | | | 0.77 | 1.76 | 0.99 | 1.20 | 0.49 | | 1.74 | 0.81 | 0.84 |
| expanded50p5l2 | | 0.36 | 0.77 | 1.76 | 0.98 | 1.20 | 0.45 | 0.97 | 1.74 | 0.81 | 0.84 |
| expanded51 | | | 1.54 | 3.49 | 1.22 | 4.15 | 0.75 | | 2.87 | 2.87 | 0.71 |
| expanded51p3 | | | 0.68 | 1.75 | 0.72 | 1.80 | 0.49 | | 1.75 | 0.75 | 0.70 |
| expanded51p5 | | | 0.91 | 2.33 | 0.89 | 1.21 | 0.46 | | 2.73 | 0.84 | 0.81 |
| expanded51p5l2 | | 0.58 | 0.91 | 2.33 | 0.90 | 1.21 | 0.47 | 0.98 | 2.73 | 0.84 | 0.81 |
| expanded52 | | | 1.46 | 2.36 | 0.99 | 2.92 | 0.76 | | 2.84 | 2.84 | 0.68 |

Continued on next page

**Table 7 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| expanded52p3 | | | 0.53 | 1.73 | 0.50 | 1.93 | 0.51 | | 1.73 | 0.78 | 0.49 |
| expanded52p5 | | | 0.66 | 2.24 | 0.62 | 0.84 | 0.47 | | 2.59 | 0.82 | 0.63 |
| expanded52p5l2 | | | 0.66 | 2.24 | 0.57 | 0.84 | 0.45 | | 2.59 | 0.82 | 0.63 |
| expanded53 | | | 1.45 | 2.81 | 0.98 | 3.29 | 0.81 | | 2.84 | 2.84 | 0.67 |
| expanded53p3 | | | 1.06 | 1.92 | 0.69 | 2.37 | 0.51 | | 1.92 | 1.52 | 0.68 |
| expanded53p5 | | | 0.64 | 2.23 | 1.00 | 1.17 | 0.48 | | 2.24 | 1.17 | 0.79 |
| expanded53p5l2 | | 0.35 | 0.63 | 2.23 | 1.01 | 1.17 | 0.52 | 0.87 | 2.24 | 1.17 | 0.79 |
| expanded54 | | | 0.41 | 2.89 | 0.50 | 3.44 | 0.73 | | 2.82 | 2.82 | 0.58 |
| expanded54p3 | | | 0.61 | 1.68 | 0.60 | 1.99 | 0.59 | | 1.68 | 1.37 | 0.65 |
| expanded54p5 | | | 0.81 | 1.61 | 0.67 | 1.17 | 0.48 | | 1.58 | 1.09 | 0.77 |
| expanded54p5l2 | | 0.66 | 0.81 | 1.61 | 0.65 | 1.17 | 0.45 | 0.74 | 1.58 | 1.09 | 0.75 |
| expanded55 | | | 0.52 | 3.83 | 0.50 | 4.30 | 0.72 | | 2.78 | 2.78 | 0.59 |
| expanded55p3 | | | 0.80 | 1.69 | 0.63 | 2.09 | 0.59 | | 1.69 | 0.84 | 0.68 |
| expanded55p5 | | | 0.82 | 1.81 | 0.58 | 1.34 | 0.54 | | 1.77 | 1.01 | 0.78 |
| expanded55p5l2 | | 0.67 | 0.81 | 1.81 | 0.58 | 1.34 | 0.55 | 0.74 | 1.77 | 1.01 | 0.78 |
| expanded56 | | | 0.48 | 3.84 | 0.47 | 4.30 | 0.67 | | 2.78 | 2.78 | 0.58 |
| expanded56p3 | | | 1.01 | 1.04 | 0.32 | 1.67 | 0.55 | | 1.04 | 0.65 | 0.65 |
| expanded56p5 | | | 0.91 | 1.96 | 0.38 | 0.86 | 0.61 | | 1.99 | 1.81 | 0.71 |
| expanded56p5l2 | | 0.35 | 0.91 | 1.96 | 0.37 | 0.86 | 0.64 | 0.72 | 1.99 | 1.81 | 0.71 |
| expanded57 | | | 0.46 | 3.84 | 0.48 | 4.30 | 0.78 | | 2.78 | 2.78 | 0.58 |
| expanded57p3 | | | 1.01 | 1.04 | 0.30 | 1.67 | 0.53 | | 1.04 | 0.65 | 0.66 |
| expanded57p5 | | | 0.91 | 1.96 | 0.38 | 0.86 | 0.62 | | 1.99 | 1.81 | 0.71 |
| expanded57p5l2 | | 0.36 | 0.92 | 1.96 | 0.38 | 0.86 | 0.62 | 0.72 | 1.99 | 1.81 | 0.71 |
| expanded58 | | | 0.56 | 3.84 | 0.47 | 4.30 | 0.82 | | 2.78 | 2.78 | 0.58 |
| expanded58p3 | | | 1.02 | 1.04 | 0.31 | 1.67 | 0.53 | | 1.04 | 0.65 | 0.66 |
| expanded58p5 | | | 0.91 | 1.96 | 0.37 | 0.86 | 0.59 | | 1.99 | 1.81 | 0.71 |
| expanded58p5l2 | | 0.54 | 0.91 | 1.96 | 0.39 | 0.86 | 0.62 | 0.72 | 1.99 | 1.81 | 0.71 |
| expanded85 | | | 0.82 | 1.69 | 0.41 | 1.67 | 0.70 | | 2.19 | 2.19 | 0.51 |
| expanded85p3 | | | 1.04 | 1.45 | 0.74 | 1.36 | 0.59 | | 1.51 | 0.90 | 0.75 |
| expanded85p5 | | | 0.89 | 1.10 | 0.68 | 1.06 | 0.56 | | 1.14 | 1.08 | 0.77 |
| expanded85p5l2 | | 0.40 | 0.89 | 1.10 | 0.70 | 1.06 | 0.50 | 0.78 | 1.14 | 1.08 | 0.77 |
| expanded87 | | | 0.92 | 1.21 | 0.35 | 1.23 | 0.75 | | 2.19 | 2.19 | 0.51 |
| expanded87p3 | | | 0.92 | 1.30 | 0.53 | 1.13 | 0.57 | | 1.35 | 1.00 | 0.73 |
| expanded87p5 | | | 1.07 | 1.18 | 0.64 | 1.38 | 0.57 | | 1.18 | 1.13 | 0.75 |
| expanded87p5l2 | | 0.40 | 1.07 | 1.18 | 0.66 | 1.38 | 0.59 | 0.77 | 1.18 | 1.13 | 0.75 |
| expanded90 | | | 1.01 | 1.62 | 0.36 | 1.61 | 0.69 | | 2.19 | 2.19 | 0.50 |
| expanded90p3 | | | 1.03 | 1.10 | 0.74 | 1.07 | 0.62 | | 1.11 | 0.91 | 0.77 |
| expanded90p5 | | | 0.96 | 0.96 | 0.64 | 1.08 | 0.59 | | 0.95 | 0.75 | 0.74 |
| expanded90p5l2 | | 0.52 | 0.96 | 0.96 | 0.66 | 1.08 | 0.58 | 0.79 | 0.95 | 0.75 | 0.74 |
| expanded91 | | | 0.95 | 1.79 | 0.34 | 1.80 | 0.79 | | 2.18 | 2.18 | 0.50 |
| expanded91p3 | | | 1.03 | 1.09 | 0.80 | 1.07 | 0.59 | | 1.10 | 0.91 | 0.78 |
| expanded91p5 | | | 1.02 | 1.05 | 0.72 | 1.06 | 0.63 | | 1.05 | 0.65 | 0.77 |
| expanded91p5l2 | | 0.54 | 1.02 | 1.05 | 0.73 | 1.06 | 0.62 | 0.80 | 1.05 | 0.65 | 0.76 |
| expanded92 | | | 0.90 | 1.81 | 0.30 | 1.82 | 0.74 | | 2.18 | 2.18 | 0.49 |
| expanded92p3 | | | 1.03 | 1.08 | 0.73 | 1.10 | 0.56 | | 1.09 | 0.91 | 0.74 |
| expanded92p5 | | | 0.96 | 1.11 | 0.69 | 1.11 | 0.60 | | 1.11 | 0.66 | 0.74 |
| expanded92p5l2 | | 0.50 | 0.96 | 1.11 | 0.72 | 1.11 | 0.58 | 0.76 | 1.11 | 0.66 | 0.74 |
| human1 | 0.55 | 0.49 | 0.87 | 2.73 | 0.72 | 2.76 | 0.53 | | 1.32 | 1.22 | 0.65 |
| baseline35 | | 0.35 | 1.42 | 14.99 | 1.25 | 14.99 | 0.70 | 0.89 | 9.58 | 9.57 | 0.76 |
| baseline35p3 | 1.18 | 0.43 | 1.13 | 2.24 | 1.23 | 2.24 | 1.53 | 1.39 | 2.24 | 1.92 | 1.09 |
| baseline35p5 | 0.68 | 0.43 | 1.02 | 1.98 | 1.25 | 1.98 | 0.97 | 1.25 | 2.25 | 1.69 | 1.04 |
| baseline36 | | 0.36 | 1.44 | 14.67 | 1.30 | 14.67 | 0.66 | 0.88 | 9.18 | 9.18 | 0.80 |
| baseline36p3 | 1.14 | 0.43 | 0.96 | 1.93 | 1.39 | 1.93 | 1.55 | 1.42 | 1.93 | 2.13 | 1.26 |
| baseline36p5 | 0.74 | 0.47 | 0.96 | 2.52 | 1.60 | 2.52 | 0.89 | 1.24 | 2.54 | 2.03 | 1.20 |
| baseline37 | | 0.36 | 1.47 | 14.67 | 1.29 | 14.67 | 0.73 | 0.83 | 9.18 | 9.18 | 0.80 |
| baseline37p3 | 1.19 | 0.43 | 0.96 | 1.93 | 1.35 | 1.93 | 1.63 | 1.43 | 1.93 | 2.13 | 1.25 |
| baseline37p5 | 0.75 | 0.42 | 0.97 | 2.52 | 1.58 | 2.52 | 0.84 | 1.15 | 2.54 | 2.03 | 1.20 |
| baseline38 | | 0.36 | 1.46 | 14.67 | 1.30 | 14.67 | 0.71 | 0.87 | 9.18 | 9.18 | 0.82 |
| baseline38p3 | 1.12 | 0.38 | 0.96 | 1.93 | 1.35 | 1.93 | 1.61 | 1.44 | 1.93 | 2.13 | 1.26 |
| baseline38p5 | 0.68 | 0.42 | 0.96 | 2.52 | 1.56 | 2.52 | 0.86 | 1.24 | 2.54 | 2.03 | 1.20 |
| baseline39 | | 0.36 | 1.46 | 14.67 | 1.30 | 14.67 | 0.69 | 0.76 | 9.18 | 9.18 | 0.82 |
| baseline39p3 | 1.06 | 0.38 | 0.96 | 1.93 | 1.37 | 1.93 | 1.58 | 1.18 | 1.93 | 2.13 | 1.24 |
| baseline39p5 | 0.71 | 0.41 | 0.97 | 2.52 | 1.57 | 2.52 | 0.89 | 1.08 | 2.54 | 2.03 | 1.19 |
| baseline40 | | 0.62 | 1.44 | 14.07 | 1.32 | 14.07 | 0.67 | 0.75 | 9.38 | 9.37 | 0.82 |
| baseline40p3 | 1.12 | 0.38 | 1.37 | 2.01 | 1.47 | 2.01 | 1.63 | 1.19 | 2.01 | 2.15 | 1.35 |
| baseline40p5 | 0.65 | 0.41 | 1.38 | 4.55 | 1.76 | 4.55 | 1.32 | 1.07 | 4.65 | 2.60 | 1.34 |
| baseline41 | | 0.62 | 1.48 | 14.09 | 1.30 | 14.09 | 0.81 | 0.74 | 9.33 | 9.32 | 0.82 |
| baseline41p3 | 0.62 | 0.51 | 1.18 | 2.60 | 1.29 | 2.60 | 0.39 | 1.06 | 2.60 | 1.15 | 0.80 |
| baseline41p5 | 0.66 | 0.38 | 0.75 | 2.76 | 1.16 | 2.76 | 0.37 | 0.95 | 2.73 | 1.21 | 0.74 |
| baseline43 | | 0.61 | 1.48 | 9.12 | 1.29 | 9.12 | 0.76 | 0.82 | 4.91 | 4.91 | 0.84 |

Continued on next page

**Table 7 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline43p3 | 0.82 | 0.44 | 1.02 | 3.08 | 1.32 | 3.08 | 0.47 | 1.07 | 3.08 | 1.00 | 0.81 |
| baseline43p5 | 0.72 | 0.36 | 1.02 | 3.12 | 1.36 | 3.12 | 0.35 | 0.97 | 3.13 | 1.12 | 0.81 |
| baseline44 | | 0.56 | 1.45 | 8.26 | 1.28 | 8.26 | 0.77 | 0.82 | 5.37 | 5.37 | 0.84 |
| baseline44p3 | 0.77 | 0.43 | 0.96 | 3.28 | 1.32 | 3.28 | 0.42 | 1.06 | 3.28 | 1.00 | 0.84 |
| baseline44p5 | 0.78 | 0.37 | 0.95 | 2.63 | 1.21 | 2.63 | 0.41 | 0.96 | 2.64 | 0.92 | 0.76 |
| baseline45 | | 0.61 | 1.38 | 6.46 | 1.29 | 6.46 | 0.76 | 0.89 | 5.36 | 5.36 | 0.79 |
| baseline45p3 | 0.73 | 0.41 | 1.40 | 2.67 | 1.21 | 2.67 | 0.41 | 1.21 | 2.67 | 0.92 | 0.87 |
| baseline45p5 | 0.69 | 0.38 | 1.44 | 3.76 | 1.35 | 3.76 | 0.38 | 1.05 | 3.77 | 0.94 | 0.86 |
| baseline46 | | 0.61 | 1.37 | 6.34 | 1.29 | 6.34 | 0.77 | 0.80 | 5.35 | 5.35 | 0.76 |
| baseline46p3 | 0.81 | 0.45 | 1.36 | 2.01 | 1.20 | 2.01 | 0.40 | 1.11 | 2.01 | 0.83 | 0.79 |
| baseline46p5 | 0.76 | 0.37 | 1.31 | 3.70 | 1.36 | 3.70 | 0.33 | 0.99 | 3.71 | 0.94 | 0.82 |
| baseline47 | | 0.61 | 1.50 | 6.69 | 1.23 | 6.69 | 0.80 | 0.79 | 5.30 | 5.30 | 0.71 |
| baseline47p3 | 0.80 | 0.42 | 1.34 | 2.17 | 1.18 | 2.17 | 0.35 | 1.10 | 2.17 | 0.77 | 0.79 |
| baseline47p5 | 0.71 | 0.37 | 1.33 | 3.84 | 1.27 | 3.84 | 0.36 | 0.97 | 3.85 | 0.90 | 0.81 |
| baseline48 | | 0.55 | 1.48 | 5.10 | 1.22 | 5.10 | 0.76 | 0.80 | 5.31 | 5.31 | 0.70 |
| baseline48p3 | 0.72 | 0.41 | 1.29 | 2.23 | 1.21 | 2.23 | 0.41 | 1.13 | 2.23 | 0.76 | 0.84 |
| baseline48p5 | 0.73 | 0.38 | 1.26 | 3.18 | 1.24 | 3.18 | 0.41 | 0.97 | 3.22 | 0.91 | 0.86 |
| baseline49 | | 0.58 | 1.44 | 4.79 | 1.21 | 4.79 | 0.79 | 0.79 | 5.25 | 5.24 | 0.73 |
| baseline49p3 | 0.66 | 0.42 | 1.05 | 2.28 | 1.00 | 2.28 | 0.42 | 1.12 | 2.28 | 0.72 | 0.78 |
| baseline49p5 | 0.59 | 0.39 | 1.18 | 3.16 | 1.05 | 3.16 | 0.37 | 0.95 | 3.20 | 0.86 | 0.82 |
| baseline50 | | 0.58 | 1.38 | 3.82 | 1.24 | 3.82 | 0.72 | 0.86 | 5.15 | 5.15 | 0.74 |
| baseline50p3 | 0.59 | 0.55 | 1.14 | 2.30 | 0.91 | 2.30 | 0.52 | 1.11 | 2.30 | 0.77 | 0.83 |
| baseline50p5 | 0.60 | 0.38 | 1.16 | 2.79 | 1.12 | 2.79 | 0.44 | 0.97 | 2.84 | 1.02 | 0.88 |
| baseline51 | | 0.56 | 1.37 | 4.33 | 1.30 | 4.33 | 0.66 | 0.89 | 5.20 | 5.20 | 0.77 |
| baseline51p3 | 0.55 | 0.41 | 1.15 | 2.26 | 0.75 | 2.26 | 0.46 | 1.12 | 2.26 | 0.79 | 0.79 |
| baseline51p5 | 0.52 | 0.38 | 1.19 | 2.74 | 0.99 | 2.74 | 0.47 | 0.98 | 2.76 | 1.04 | 0.84 |
| baseline53 | | 0.51 | 1.36 | 3.41 | 1.04 | 3.60 | 0.78 | 0.81 | 5.12 | 5.12 | 0.73 |
| baseline53p3 | 0.56 | 0.42 | 1.03 | 2.41 | 0.93 | 2.41 | 0.49 | 0.96 | 2.41 | 0.87 | 0.76 |
| baseline53p5 | 0.41 | 0.36 | 1.12 | 2.92 | 1.04 | 2.92 | 0.48 | 0.87 | 2.93 | 1.31 | 0.79 |
| baseline54 | | 0.48 | 0.43 | 3.52 | 0.43 | 3.73 | 0.73 | 0.72 | 5.08 | 5.08 | 0.61 |
| baseline54p3 | 0.51 | 0.41 | 1.04 | 1.97 | 0.88 | 1.97 | 0.58 | 0.81 | 1.97 | 0.77 | 0.75 |
| baseline54p5 | 0.47 | 0.35 | 1.05 | 3.00 | 0.93 | 3.00 | 0.44 | 0.74 | 3.01 | 1.25 | 0.80 |
| baseline55 | | 0.46 | 0.66 | 4.29 | 0.44 | 4.50 | 0.72 | 0.72 | 5.07 | 5.06 | 0.60 |
| baseline55p3 | 0.51 | 0.42 | 1.08 | 2.20 | 0.81 | 2.20 | 0.57 | 0.81 | 2.20 | 0.78 | 0.73 |
| baseline55p5 | 0.48 | 0.64 | 1.09 | 2.80 | 0.78 | 2.80 | 0.55 | 0.74 | 2.81 | 1.03 | 0.76 |
| baseline56 | | 0.47 | 0.66 | 4.32 | 0.40 | 4.52 | 0.73 | 0.71 | 5.06 | 5.06 | 0.60 |
| baseline56p3 | 0.50 | 0.43 | 1.20 | 1.68 | 0.58 | 1.68 | 0.56 | 0.80 | 1.68 | 0.74 | 0.62 |
| baseline56p5 | 0.49 | 0.37 | 0.91 | 2.29 | 0.66 | 2.29 | 0.62 | 0.72 | 2.29 | 1.15 | 0.64 |
| baseline57 | | 0.47 | 0.54 | 4.32 | 0.42 | 4.52 | 0.78 | 0.71 | 5.06 | 5.06 | 0.60 |
| baseline57p3 | 0.50 | 0.43 | 1.20 | 1.68 | 0.58 | 1.68 | 0.55 | 0.80 | 1.68 | 0.74 | 0.61 |
| baseline57p5 | 0.51 | 0.37 | 0.91 | 2.29 | 0.64 | 2.29 | 0.62 | 0.72 | 2.29 | 1.15 | 0.64 |
| baseline58 | | 0.47 | 0.48 | 4.32 | 0.42 | 4.52 | 0.75 | 0.71 | 5.06 | 5.06 | 0.60 |
| baseline58p3 | 0.56 | 0.43 | 1.20 | 1.68 | 0.58 | 1.68 | 0.53 | 0.80 | 1.68 | 0.74 | 0.62 |
| baseline58p5 | 0.51 | 0.36 | 0.91 | 2.29 | 0.63 | 2.29 | 0.66 | 0.72 | 2.29 | 1.15 | 0.64 |
| baseline85 | | 0.27 | 0.99 | 1.76 | 0.36 | 1.77 | 0.69 | 0.72 | 3.80 | 3.80 | 0.50 |
| baseline85p3 | 0.48 | 0.36 | 1.04 | 1.22 | 0.50 | 1.22 | 0.63 | 0.88 | 1.22 | 0.73 | 0.66 |
| baseline85p5 | 0.51 | 0.40 | 0.89 | 1.43 | 0.60 | 1.43 | 0.52 | 0.78 | 1.43 | 1.37 | 0.72 |
| baseline87 | | 0.28 | 1.06 | 1.28 | 0.29 | 1.26 | 0.72 | 0.71 | 3.79 | 3.79 | 0.49 |
| baseline87p3 | 0.52 | 0.37 | 0.93 | 1.13 | 0.51 | 1.13 | 0.60 | 0.86 | 1.13 | 0.72 | 0.63 |
| baseline87p5 | 0.54 | 0.40 | 1.08 | 1.47 | 0.60 | 1.47 | 0.60 | 0.77 | 1.47 | 0.94 | 0.69 |
| baseline90 | | 0.38 | 0.98 | 1.67 | 0.29 | 1.62 | 0.74 | 0.70 | 3.82 | 3.82 | 0.50 |
| baseline90p3 | 0.52 | 0.36 | 0.86 | 1.10 | 0.59 | 1.10 | 0.62 | 0.86 | 1.10 | 0.76 | 0.65 |
| baseline90p5 | 0.53 | 0.53 | 0.75 | 1.05 | 0.67 | 1.05 | 0.61 | 0.79 | 1.05 | 0.85 | 0.68 |
| baseline91 | | 0.28 | 1.14 | 1.84 | 0.30 | 1.81 | 0.74 | 0.71 | 3.80 | 3.80 | 0.49 |
| baseline91p3 | 0.52 | 0.36 | 0.87 | 1.10 | 0.70 | 1.10 | 0.59 | 0.87 | 1.10 | 0.77 | 0.69 |
| baseline91p5 | 0.50 | 0.55 | 0.84 | 1.06 | 0.79 | 1.06 | 0.60 | 0.80 | 1.06 | 0.86 | 0.70 |
| baseline92 | | 0.28 | 1.03 | 1.86 | 0.25 | 1.83 | 0.69 | 0.68 | 3.77 | 3.77 | 0.47 |
| baseline92p3 | 0.49 | 0.37 | 1.03 | 1.14 | 0.69 | 1.14 | 0.58 | 0.84 | 1.14 | 0.75 | 0.64 |
| baseline92p5 | 0.46 | 0.51 | 0.95 | 1.09 | 0.76 | 1.09 | 0.60 | 0.76 | 1.09 | 0.90 | 0.68 |

**Source:** Own elaboration.

**Notes:** Each specification name encodes four attributes. The prefix indicates the flattening approach: *baseline* uses baseline flattening (three lags); *expanded* applies extended flattening (four or five lags). *baseline** shares the same baseline flattening as *baseline* but is used as a prefix to easily identify the best-performing variable grouping from the pre-selection exercise. The number following the prefix (e.g., 35, 40, 52) identifies the variable grouping. Suffixes *p3* and *p5* indicate PCA retaining 3 or 5 components; *l2* denotes two autoregressive lags of GDP; the absence of these suffixes indicates no dimensionality reduction and no autoregressive lags. *human1* refers to a judgment-based specification constructed by the authors and does not follow this naming convention. See Section 3.2 for a full description of specifications.

Table 8: RMSE across specifications and models (vintage $p = 2$)

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline*52 | | 0.51 | 0.99 | 4.86 | 0.58 | 4.86 | 0.73 | 0.75 | 5.04 | 5.04 | 0.47 |
| baseline*52p3 | 0.54 | 0.42 | 0.86 | 2.07 | 0.69 | 2.07 | 0.49 | 0.97 | 2.07 | 0.75 | 0.61 |
| baseline*52p5 | 0.51 | 0.36 | 0.83 | 1.80 | 0.82 | 1.80 | 0.44 | 0.88 | 1.81 | 0.88 | 0.70 |
| baseline*52p5l2 | | 0.34 | | | | | | 0.88 | | | |
| expanded35 | | | 1.16 | 13.85 | 0.65 | 13.07 | 0.67 | | 3.76 | 3.76 | 0.42 |
| expanded35p3 | | | 0.88 | 2.99 | 1.46 | 2.59 | 1.73 | | 2.99 | 2.43 | 1.25 |
| expanded35p5 | | | 0.85 | 1.33 | 1.40 | 2.88 | 1.07 | | 1.41 | 1.91 | 1.22 |
| expanded35p5l2 | | 0.42 | 0.83 | 1.33 | 1.42 | 2.88 | 1.03 | 1.25 | 1.41 | 1.91 | 1.22 |
| expanded36 | | | 1.12 | 12.96 | 0.66 | 11.74 | 0.72 | | 3.79 | 3.79 | 0.55 |
| expanded36p3 | | | 0.93 | 2.89 | 1.41 | 2.31 | 1.63 | | 2.89 | 2.46 | 1.52 |
| expanded36p5 | | | 0.74 | 3.02 | 1.39 | 4.25 | 0.86 | | 3.42 | 1.85 | 1.35 |
| expanded36p5l2 | | 0.42 | 0.75 | 3.02 | 1.40 | 4.25 | 0.89 | 1.24 | 3.42 | 1.85 | 1.35 |
| expanded37 | | | 1.11 | 12.96 | 0.65 | 11.74 | 0.69 | | 3.79 | 3.79 | 0.56 |
| expanded37p3 | | | 0.94 | 2.89 | 1.42 | 2.31 | 1.68 | | 2.89 | 2.46 | 1.52 |
| expanded37p5 | | | 0.77 | 3.02 | 1.38 | 4.25 | 0.88 | | 3.42 | 1.85 | 1.35 |
| expanded37p5l2 | | 0.42 | 0.75 | 3.02 | 1.39 | 4.25 | 0.87 | 1.15 | 3.42 | 1.85 | 1.35 |
| expanded38 | | | 1.17 | 12.96 | 0.65 | 11.74 | 0.73 | | 3.79 | 3.79 | 0.55 |
| expanded38p3 | | | 0.92 | 2.89 | 1.38 | 2.31 | 1.65 | | 2.89 | 2.46 | 1.53 |
| expanded38p5 | | | 0.75 | 3.02 | 1.40 | 4.25 | 0.87 | | 3.42 | 1.85 | 1.35 |
| expanded38p5l2 | | 0.43 | 0.71 | 3.02 | 1.40 | 4.25 | 0.91 | 1.24 | 3.42 | 1.85 | 1.35 |
| expanded39 | | | 1.20 | 12.96 | 0.63 | 11.74 | 0.69 | | 3.79 | 3.79 | 0.54 |
| expanded39p3 | | | 0.89 | 2.89 | 1.41 | 2.31 | 1.71 | | 2.89 | 2.46 | 1.53 |
| expanded39p5 | | | 0.74 | 3.02 | 1.37 | 4.25 | 0.81 | | 3.42 | 1.85 | 1.37 |
| expanded39p5l2 | | 0.61 | 0.72 | 3.02 | 1.40 | 4.25 | 0.96 | 1.08 | 3.42 | 1.85 | 1.34 |
| expanded40 | | | 1.14 | 11.80 | 0.67 | 10.78 | 0.71 | | 3.71 | 3.71 | 0.54 |
| expanded40p3 | | | 0.99 | 3.51 | 1.65 | 2.93 | 1.75 | | 3.51 | 3.09 | 1.49 |
| expanded40p5 | | | 1.01 | 5.19 | 1.92 | 5.47 | 1.54 | | 5.52 | 2.81 | 1.60 |
| expanded40p5l2 | | 0.52 | 1.00 | 5.19 | 1.89 | 5.47 | 1.54 | 1.07 | 5.52 | 2.81 | 1.59 |
| expanded41 | | | 1.14 | 11.34 | 0.66 | 10.55 | 0.78 | | 3.75 | 3.75 | 0.54 |
| expanded41p3 | | | 1.09 | 1.00 | 0.76 | 0.76 | 0.43 | | 1.00 | 0.74 | 0.72 |
| expanded41p5 | | | 0.98 | 2.26 | 0.81 | 2.16 | 0.40 | | 5.15 | 0.88 | 0.79 |
| expanded41p5l2 | | 0.39 | 0.95 | 2.26 | 0.78 | 2.16 | 0.39 | 0.95 | 5.15 | 0.88 | 0.78 |
| expanded43 | | | 1.02 | 9.43 | 0.62 | 8.84 | 0.72 | | 2.57 | 2.57 | 0.44 |
| expanded43p3 | | | 1.43 | 2.23 | 1.53 | 2.34 | 0.98 | | 2.23 | 1.56 | 1.00 |
| expanded43p5 | | | 1.45 | 1.89 | 1.62 | 3.91 | 0.69 | | 1.96 | 1.36 | 0.98 |
| expanded43p5l2 | | 0.37 | 1.44 | 1.89 | 1.60 | 3.91 | 0.70 | 0.97 | 1.96 | 1.36 | 0.99 |
| expanded44 | | | 1.10 | 8.89 | 0.64 | 8.57 | 0.70 | | 2.86 | 2.86 | 0.44 |
| expanded44p3 | | | 1.10 | 1.73 | 1.22 | 1.54 | 0.44 | | 1.73 | 0.74 | 0.70 |
| expanded44p5 | | | 1.21 | 3.18 | 1.37 | 2.83 | 0.34 | | 6.51 | 0.58 | 0.69 |
| expanded44p5l2 | | 0.37 | 1.18 | 3.18 | 1.38 | 2.83 | 0.36 | 0.96 | 6.51 | 0.58 | 0.70 |
| expanded45 | | | 0.78 | 8.38 | 0.68 | 8.17 | 0.71 | | 2.84 | 2.84 | 0.45 |
| expanded45p3 | | | 1.08 | 1.53 | 1.00 | 1.32 | 0.37 | | 1.53 | 0.63 | 0.82 |
| expanded45p5 | | | 1.01 | 2.67 | 1.22 | 3.12 | 0.35 | | 4.08 | 0.64 | 0.84 |
| expanded45p5l2 | | 0.37 | 1.01 | 2.67 | 1.22 | 3.12 | 0.37 | 1.05 | 4.08 | 0.64 | 0.85 |
| expanded46 | | | 0.91 | 8.35 | 0.66 | 8.15 | 0.69 | | 2.83 | 2.83 | 0.48 |
| expanded46p3 | | | 2.21 | 1.39 | 1.55 | 1.10 | 0.38 | | 1.39 | 0.64 | 1.17 |
| expanded46p5 | | | 1.94 | 2.38 | 1.63 | 2.70 | 0.42 | | 2.63 | 0.71 | 1.06 |
| expanded46p5l2 | | 0.37 | 1.94 | 2.38 | 1.66 | 2.70 | 0.41 | 0.99 | 2.63 | 0.71 | 1.08 |
| expanded47 | | | 1.47 | 8.60 | 0.68 | 8.59 | 0.76 | | 2.77 | 2.77 | 0.52 |
| expanded47p3 | | | 2.01 | 1.46 | 1.55 | 1.11 | 0.38 | | 1.46 | 0.65 | 1.16 |
| expanded47p5 | | | 2.03 | 2.34 | 1.66 | 2.35 | 0.38 | | 2.48 | 0.70 | 1.10 |
| expanded47p5l2 | | 0.37 | 1.93 | 2.34 | 1.65 | 2.35 | 0.39 | 0.97 | 2.48 | 0.70 | 1.08 |
| expanded48 | | | 1.52 | 6.34 | 0.67 | 6.44 | 0.81 | | 2.79 | 2.79 | 0.52 |
| expanded48p3 | | | 1.95 | 1.41 | 1.70 | 1.08 | 0.41 | | 1.41 | 0.67 | 1.24 |
| expanded48p5 | | | 1.82 | 2.02 | 1.84 | 1.79 | 0.39 | | 2.06 | 0.69 | 1.20 |
| expanded48p5l2 | | 0.37 | 1.86 | 2.02 | 1.84 | 1.79 | 0.36 | 0.97 | 2.06 | 0.69 | 1.22 |
| expanded49 | | | 1.19 | 6.06 | 0.64 | 6.24 | 0.72 | | 2.80 | 2.80 | 0.44 |
| expanded49p3 | | | 1.84 | 1.12 | 1.59 | 1.21 | 0.39 | | 1.12 | 0.64 | 1.20 |
| expanded49p5 | | | 2.06 | 1.74 | 1.69 | 1.44 | 0.38 | | 1.78 | 0.63 | 1.18 |
| expanded49p5l2 | | 0.38 | 2.06 | 1.74 | 1.72 | 1.44 | 0.38 | 0.95 | 1.78 | 0.63 | 1.20 |
| expanded50 | | | 1.25 | 5.72 | 0.62 | 5.88 | 0.67 | | 2.76 | 2.76 | 0.45 |
| expanded50p3 | | | 0.78 | 1.24 | 0.87 | 1.34 | 0.45 | | 1.24 | 0.67 | 0.77 |
| expanded50p5 | | | 0.92 | 1.01 | 1.10 | 0.95 | 0.47 | | 1.26 | 0.66 | 0.88 |
| expanded50p5l2 | | 0.36 | 0.92 | 1.01 | 1.10 | 0.95 | 0.43 | 0.97 | 1.26 | 0.66 | 0.88 |
| expanded51 | | | 1.18 | 5.85 | 0.63 | 6.11 | 0.72 | | 2.76 | 2.76 | 0.49 |
| expanded51p3 | | | 0.86 | 1.28 | 0.85 | 1.36 | 0.47 | | 1.28 | 0.68 | 0.77 |
| expanded51p5 | | | 1.05 | 1.05 | 1.04 | 0.99 | 0.43 | | 1.11 | 0.69 | 0.89 |
| expanded51p5l2 | | 0.58 | 1.05 | 1.05 | 1.05 | 0.99 | 0.46 | 0.98 | 1.11 | 0.69 | 0.88 |
| expanded52 | | | 1.11 | 5.04 | 0.62 | 5.18 | 0.73 | | 2.73 | 2.73 | 0.48 |

Continued on next page

**Table 8 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| expanded52p3 | | | 0.59 | 1.47 | 0.59 | 1.58 | 0.51 | | 1.47 | 0.74 | 0.49 |
| expanded52p5 | | | 0.71 | 1.72 | 0.72 | 0.82 | 0.46 | | 1.84 | 0.70 | 0.62 |
| expanded52p5l2 | | | 0.70 | 1.72 | 0.70 | 0.82 | 0.43 | | 1.84 | 0.70 | 0.63 |
| expanded53 | | | 1.07 | 4.97 | 0.57 | 5.18 | 0.77 | | 2.74 | 2.74 | 0.48 |
| expanded53p3 | | | 1.09 | 1.46 | 0.62 | 1.76 | 0.49 | | 1.46 | 1.18 | 0.62 |
| expanded53p5 | | | 0.65 | 1.15 | 0.96 | 0.98 | 0.48 | | 1.17 | 0.80 | 0.73 |
| expanded53p5l2 | | 0.35 | 0.65 | 1.15 | 0.98 | 0.98 | 0.51 | 0.87 | 1.17 | 0.80 | 0.73 |
| expanded54 | | | 0.40 | 5.23 | 0.38 | 5.47 | 0.72 | | 2.72 | 2.72 | 0.40 |
| expanded54p3 | | | 0.68 | 1.28 | 0.48 | 1.47 | 0.57 | | 1.28 | 1.09 | 0.60 |
| expanded54p5 | | | 0.80 | 1.06 | 0.74 | 0.83 | 0.51 | | 1.05 | 0.78 | 0.71 |
| expanded54p5l2 | | 0.66 | 0.79 | 1.06 | 0.72 | 0.83 | 0.48 | 0.74 | 1.05 | 0.78 | 0.70 |
| expanded55 | | | 0.50 | 5.45 | 0.40 | 5.73 | 0.67 | | 2.68 | 2.68 | 0.42 |
| expanded55p3 | | | 1.00 | 1.33 | 0.59 | 1.58 | 0.57 | | 1.33 | 0.70 | 0.65 |
| expanded55p5 | | | 0.81 | 1.49 | 0.66 | 1.32 | 0.60 | | 1.49 | 0.68 | 0.76 |
| expanded55p5l2 | | 0.67 | 0.81 | 1.49 | 0.68 | 1.32 | 0.57 | 0.74 | 1.49 | 0.68 | 0.76 |
| expanded56 | | | 0.47 | 5.68 | 0.36 | 5.95 | 0.63 | | 2.68 | 2.68 | 0.41 |
| expanded56p3 | | | 1.14 | 0.88 | 0.51 | 1.34 | 0.56 | | 0.88 | 0.59 | 0.63 |
| expanded56p5 | | | 0.95 | 1.55 | 0.46 | 1.09 | 0.57 | | 1.57 | 1.60 | 0.68 |
| expanded56p5l2 | | 0.35 | 0.95 | 1.55 | 0.45 | 1.09 | 0.59 | 0.72 | 1.57 | 1.60 | 0.69 |
| expanded57 | | | 0.44 | 5.68 | 0.37 | 5.95 | 0.79 | | 2.68 | 2.68 | 0.41 |
| expanded57p3 | | | 1.16 | 0.88 | 0.51 | 1.34 | 0.54 | | 0.88 | 0.59 | 0.63 |
| expanded57p5 | | | 0.94 | 1.55 | 0.46 | 1.09 | 0.58 | | 1.57 | 1.60 | 0.69 |
| expanded57p5l2 | | 0.36 | 0.95 | 1.55 | 0.43 | 1.09 | 0.57 | 0.72 | 1.57 | 1.60 | 0.69 |
| expanded58 | | | 0.55 | 5.68 | 0.39 | 5.95 | 0.78 | | 2.68 | 2.68 | 0.41 |
| expanded58p3 | | | 1.14 | 0.88 | 0.50 | 1.34 | 0.55 | | 0.88 | 0.59 | 0.64 |
| expanded58p5 | | | 0.94 | 1.55 | 0.46 | 1.09 | 0.55 | | 1.57 | 1.60 | 0.69 |
| expanded58p5l2 | | 0.54 | 0.94 | 1.55 | 0.45 | 1.09 | 0.56 | 0.72 | 1.57 | 1.60 | 0.69 |
| expanded85 | | | 0.75 | 5.13 | 0.41 | 5.11 | 0.66 | | 2.08 | 2.08 | 0.39 |
| expanded85p3 | | | 0.77 | 1.22 | 0.67 | 1.31 | 0.56 | | 1.28 | 0.63 | 0.72 |
| expanded85p5 | | | 0.80 | 0.64 | 0.73 | 0.64 | 0.59 | | 0.87 | 0.63 | 0.74 |
| expanded85p5l2 | | 0.40 | 0.79 | 0.64 | 0.75 | 0.64 | 0.53 | 0.78 | 0.87 | 0.63 | 0.75 |
| expanded87 | | | 0.85 | 1.27 | 0.43 | 1.29 | 0.73 | | 2.08 | 2.08 | 0.39 |
| expanded87p3 | | | 0.81 | 0.95 | 0.46 | 0.82 | 0.54 | | 1.00 | 0.71 | 0.69 |
| expanded87p5 | | | 1.10 | 0.72 | 0.60 | 0.89 | 0.58 | | 0.72 | 0.73 | 0.70 |
| expanded87p5l2 | | 0.40 | 1.10 | 0.72 | 0.62 | 0.89 | 0.59 | 0.77 | 0.72 | 0.73 | 0.70 |
| expanded90 | | | 0.88 | 1.68 | 0.41 | 1.67 | 0.65 | | 2.10 | 2.10 | 0.38 |
| expanded90p3 | | | 0.72 | 0.71 | 0.46 | 0.54 | 0.59 | | 0.72 | 0.61 | 0.78 |
| expanded90p5 | | | 1.01 | 0.63 | 0.47 | 0.79 | 0.59 | | 0.63 | 0.59 | 0.73 |
| expanded90p5l2 | | 0.52 | 1.01 | 0.63 | 0.48 | 0.79 | 0.59 | 0.79 | 0.63 | 0.59 | 0.74 |
| expanded91 | | | 0.92 | 1.91 | 0.43 | 1.91 | 0.76 | | 2.09 | 2.09 | 0.38 |
| expanded91p3 | | | 0.73 | 0.70 | 0.56 | 0.54 | 0.55 | | 0.71 | 0.61 | 0.79 |
| expanded91p5 | | | 1.10 | 0.71 | 0.61 | 0.82 | 0.63 | | 0.70 | 0.53 | 0.76 |
| expanded91p5l2 | | 0.54 | 1.10 | 0.71 | 0.61 | 0.82 | 0.62 | 0.80 | 0.70 | 0.53 | 0.75 |
| expanded92 | | | 0.89 | 1.91 | 0.42 | 1.91 | 0.70 | | 2.09 | 2.09 | 0.36 |
| expanded92p3 | | | 1.34 | 0.63 | 0.52 | 0.62 | 0.52 | | 0.65 | 0.61 | 0.75 |
| expanded92p5 | | | 1.05 | 0.74 | 0.54 | 0.89 | 0.59 | | 0.71 | 0.54 | 0.73 |
| expanded92p5l2 | | 0.50 | 1.06 | 0.74 | 0.57 | 0.89 | 0.58 | 0.76 | 0.71 | 0.54 | 0.74 |
| human1 | 0.41 | 0.49 | 0.87 | 1.61 | 0.74 | 1.94 | 0.71 | | 1.18 | 1.20 | 0.63 |
| baseline35 | | 0.35 | 1.28 | 16.70 | 0.60 | 16.70 | 0.66 | 0.85 | 9.51 | 9.50 | 0.41 |
| baseline35p3 | 1.14 | 0.43 | 1.20 | 3.17 | 1.74 | 3.17 | 1.76 | 1.39 | 3.17 | 2.38 | 1.48 |
| baseline35p5 | 0.74 | 0.43 | 1.04 | 1.67 | 1.60 | 1.67 | 0.99 | 1.25 | 1.60 | 2.03 | 1.35 |
| baseline36 | | 0.36 | 1.27 | 15.59 | 0.62 | 15.59 | 0.63 | 0.84 | 9.10 | 9.09 | 0.52 |
| baseline36p3 | 1.19 | 0.43 | 1.25 | 3.23 | 1.58 | 3.23 | 1.58 | 1.42 | 3.23 | 2.39 | 1.73 |
| baseline36p5 | 0.69 | 0.47 | 1.00 | 2.84 | 1.66 | 2.84 | 0.87 | 1.24 | 2.88 | 2.02 | 1.55 |
| baseline37 | | 0.36 | 1.28 | 15.59 | 0.63 | 15.59 | 0.72 | 0.80 | 9.10 | 9.09 | 0.52 |
| baseline37p3 | 1.09 | 0.43 | 1.23 | 3.23 | 1.55 | 3.23 | 1.66 | 1.43 | 3.23 | 2.39 | 1.74 |
| baseline37p5 | 0.70 | 0.42 | 1.03 | 2.84 | 1.63 | 2.84 | 0.82 | 1.15 | 2.88 | 2.02 | 1.53 |
| baseline38 | | 0.36 | 1.31 | 15.59 | 0.63 | 15.59 | 0.69 | 0.85 | 9.10 | 9.09 | 0.53 |
| baseline38p3 | 1.04 | 0.38 | 1.21 | 3.23 | 1.58 | 3.23 | 1.68 | 1.44 | 3.23 | 2.39 | 1.73 |
| baseline38p5 | 0.67 | 0.42 | 1.07 | 2.84 | 1.62 | 2.84 | 0.88 | 1.24 | 2.88 | 2.02 | 1.54 |
| baseline39 | | 0.36 | 1.27 | 15.59 | 0.61 | 15.59 | 0.66 | 0.72 | 9.10 | 9.09 | 0.53 |
| baseline39p3 | 1.04 | 0.38 | 1.24 | 3.23 | 1.57 | 3.23 | 1.62 | 1.18 | 3.23 | 2.39 | 1.73 |
| baseline39p5 | 0.66 | 0.41 | 1.00 | 2.84 | 1.63 | 2.84 | 0.88 | 1.08 | 2.88 | 2.02 | 1.54 |
| baseline40 | | 0.64 | 1.23 | 14.85 | 0.61 | 14.85 | 0.66 | 0.70 | 9.29 | 9.28 | 0.52 |
| baseline40p3 | 1.03 | 0.38 | 1.41 | 3.25 | 1.78 | 3.25 | 1.85 | 1.19 | 3.25 | 2.60 | 1.62 |
| baseline40p5 | 0.65 | 0.41 | 1.47 | 5.22 | 2.12 | 5.22 | 1.50 | 1.07 | 5.20 | 2.99 | 1.59 |
| baseline41 | | 0.64 | 1.29 | 14.90 | 0.63 | 14.90 | 0.78 | 0.69 | 9.25 | 9.24 | 0.52 |
| baseline41p3 | 0.61 | 0.51 | 0.88 | 1.90 | 0.89 | 1.90 | 0.44 | 1.06 | 1.90 | 1.11 | 0.81 |
| baseline41p5 | 0.68 | 0.38 | 0.88 | 2.96 | 0.94 | 2.96 | 0.38 | 0.95 | 2.88 | 1.06 | 0.79 |
| baseline43 | | 0.63 | 1.17 | 10.89 | 0.58 | 10.89 | 0.74 | 0.80 | 4.81 | 4.81 | 0.43 |

Continued on next page

**Table 8 – continued**

| Specification | BVAR | DFM | DT | ENET | GBT | LASSO | LSTM | MIDAS | OLS | OLSR | RF |
|---|---|---|---|---|---|---|---|---|---|---|---|
| baseline43p3 | 0.80 | 0.44 | 2.30 | 2.43 | 1.74 | 2.43 | 0.98 | 1.07 | 2.43 | 1.37 | 1.06 |
| baseline43p5 | 0.82 | 0.36 | 1.61 | 3.45 | 1.77 | 3.45 | 0.72 | 0.97 | 3.45 | 1.31 | 1.02 |
| baseline44 | | 0.58 | 1.13 | 9.99 | 0.61 | 9.99 | 0.73 | 0.79 | 5.28 | 5.28 | 0.43 |
| baseline44p3 | 0.76 | 0.43 | 1.70 | 2.43 | 1.26 | 2.43 | 0.42 | 1.06 | 2.43 | 0.89 | 0.83 |
| baseline44p5 | 0.78 | 0.37 | 1.12 | 1.92 | 1.51 | 1.92 | 0.39 | 0.96 | 1.91 | 0.76 | 0.78 |
| baseline45 | | 0.63 | 0.77 | 9.12 | 0.63 | 9.12 | 0.72 | 0.84 | 5.27 | 5.26 | 0.44 |
| baseline45p3 | 0.79 | 0.41 | 1.15 | 2.05 | 1.32 | 2.05 | 0.40 | 1.21 | 2.06 | 0.83 | 0.89 |
| baseline45p5 | 0.69 | 0.38 | 1.22 | 3.26 | 1.52 | 3.26 | 0.37 | 1.05 | 3.27 | 0.86 | 0.89 |
| baseline46 | | 0.62 | 0.74 | 9.06 | 0.65 | 9.06 | 0.72 | 0.77 | 5.26 | 5.26 | 0.47 |
| baseline46p3 | 0.78 | 0.45 | 2.18 | 1.59 | 1.76 | 1.59 | 0.39 | 1.11 | 1.59 | 0.75 | 1.21 |
| baseline46p5 | 0.67 | 0.37 | 2.25 | 3.15 | 1.73 | 3.15 | 0.37 | 0.99 | 3.15 | 0.89 | 1.14 |
| baseline47 | | 0.62 | 1.35 | 9.16 | 0.67 | 9.16 | 0.76 | 0.76 | 5.21 | 5.21 | 0.52 |
| baseline47p3 | 0.79 | 0.42 | 2.15 | 1.68 | 1.80 | 1.68 | 0.35 | 1.10 | 1.68 | 0.71 | 1.18 |
| baseline47p5 | 0.76 | 0.37 | 2.17 | 3.24 | 1.78 | 3.24 | 0.37 | 0.97 | 3.24 | 0.85 | 1.13 |
| baseline48 | | 0.57 | 1.27 | 6.42 | 0.64 | 6.42 | 0.73 | 0.77 | 5.23 | 5.23 | 0.52 |
| baseline48p3 | 0.77 | 0.41 | 2.13 | 1.80 | 1.90 | 1.80 | 0.40 | 1.13 | 1.80 | 0.69 | 1.28 |
| baseline48p5 | 0.72 | 0.38 | 2.04 | 2.64 | 1.80 | 2.64 | 0.38 | 0.97 | 2.67 | 0.83 | 1.25 |
| baseline49 | | 0.60 | 1.13 | 6.21 | 0.57 | 6.21 | 0.79 | 0.76 | 5.18 | 5.18 | 0.46 |
| baseline49p3 | 0.69 | 0.42 | 1.96 | 1.83 | 1.76 | 1.83 | 0.40 | 1.12 | 1.83 | 0.65 | 1.24 |
| baseline49p5 | 0.66 | 0.39 | 2.04 | 2.65 | 1.65 | 2.65 | 0.35 | 0.95 | 2.68 | 0.77 | 1.22 |
| baseline50 | | 0.59 | 1.02 | 5.75 | 0.59 | 5.75 | 0.69 | 0.81 | 5.09 | 5.09 | 0.45 |
| baseline50p3 | 0.56 | 0.55 | 1.20 | 1.94 | 1.02 | 1.94 | 0.49 | 1.11 | 1.94 | 0.69 | 0.85 |
| baseline50p5 | 0.58 | 0.38 | 1.21 | 2.25 | 1.25 | 2.25 | 0.43 | 0.97 | 2.30 | 0.98 | 0.93 |
| baseline51 | | 0.57 | 1.00 | 5.95 | 0.55 | 5.95 | 0.64 | 0.83 | 5.13 | 5.13 | 0.48 |
| baseline51p3 | 0.58 | 0.41 | 1.31 | 1.97 | 0.94 | 1.97 | 0.44 | 1.12 | 1.97 | 0.70 | 0.87 |
| baseline51p5 | 0.54 | 0.38 | 1.22 | 2.19 | 1.25 | 2.19 | 0.44 | 0.98 | 2.21 | 1.00 | 0.92 |
| baseline53 | | 0.52 | 1.04 | 4.84 | 0.57 | 4.97 | 0.70 | 0.77 | 5.05 | 5.05 | 0.46 |
| baseline53p3 | 0.52 | 0.42 | 1.30 | 2.13 | 0.71 | 2.13 | 0.47 | 0.96 | 2.13 | 0.73 | 0.70 |
| baseline53p5 | 0.48 | 0.36 | 1.16 | 2.26 | 0.88 | 2.26 | 0.49 | 0.87 | 2.27 | 1.16 | 0.72 |
| baseline54 | | 0.49 | 0.44 | 5.12 | 0.34 | 5.25 | 0.70 | 0.66 | 5.01 | 5.01 | 0.39 |
| baseline54p3 | 0.50 | 0.41 | 1.48 | 1.72 | 0.64 | 1.72 | 0.56 | 0.81 | 1.72 | 0.62 | 0.73 |
| baseline54p5 | 0.48 | 0.35 | 1.17 | 2.22 | 0.78 | 2.22 | 0.46 | 0.74 | 2.23 | 1.10 | 0.77 |
| baseline55 | | 0.47 | 0.68 | 5.60 | 0.34 | 5.75 | 0.72 | 0.67 | 4.99 | 4.99 | 0.38 |
| baseline55p3 | 0.53 | 0.42 | 1.49 | 1.98 | 0.65 | 1.98 | 0.57 | 0.81 | 1.98 | 0.63 | 0.72 |
| baseline55p5 | 0.52 | 0.64 | 1.16 | 2.41 | 0.70 | 2.41 | 0.60 | 0.74 | 2.41 | 0.87 | 0.77 |
| baseline56 | | 0.47 | 0.67 | 5.83 | 0.36 | 5.97 | 0.66 | 0.66 | 4.99 | 4.99 | 0.39 |
| baseline56p3 | 0.53 | 0.43 | 1.39 | 1.52 | 0.72 | 1.52 | 0.57 | 0.80 | 1.52 | 0.67 | 0.60 |
| baseline56p5 | 0.48 | 0.37 | 1.04 | 2.37 | 0.77 | 2.37 | 0.58 | 0.72 | 2.37 | 1.04 | 0.63 |
| baseline57 | | 0.47 | 0.55 | 5.83 | 0.33 | 5.97 | 0.73 | 0.66 | 4.99 | 4.99 | 0.39 |
| baseline57p3 | 0.51 | 0.43 | 1.39 | 1.52 | 0.73 | 1.52 | 0.55 | 0.80 | 1.52 | 0.67 | 0.60 |
| baseline57p5 | 0.49 | 0.37 | 1.04 | 2.37 | 0.76 | 2.37 | 0.60 | 0.72 | 2.37 | 1.04 | 0.63 |
| baseline58 | | 0.47 | 0.49 | 5.83 | 0.34 | 5.97 | 0.73 | 0.66 | 4.99 | 4.99 | 0.39 |
| baseline58p3 | 0.50 | 0.43 | 1.39 | 1.52 | 0.73 | 1.52 | 0.54 | 0.80 | 1.52 | 0.67 | 0.61 |
| baseline58p5 | 0.51 | 0.36 | 1.04 | 2.37 | 0.76 | 2.37 | 0.59 | 0.72 | 2.37 | 1.04 | 0.63 |
| baseline85 | | 0.29 | 0.77 | 5.03 | 0.38 | 5.03 | 0.65 | 0.72 | 3.72 | 3.72 | 0.37 |
| baseline85p3 | 0.49 | 0.36 | 0.75 | 0.92 | 0.48 | 0.92 | 0.60 | 0.88 | 0.92 | 0.64 | 0.64 |
| baseline85p5 | 0.55 | 0.40 | 0.66 | 1.17 | 0.63 | 1.17 | 0.55 | 0.78 | 1.17 | 1.08 | 0.71 |
| baseline87 | | 0.29 | 0.85 | 1.20 | 0.44 | 1.23 | 0.70 | 0.71 | 3.71 | 3.71 | 0.36 |
| baseline87p3 | 0.49 | 0.37 | 0.70 | 0.87 | 0.42 | 0.87 | 0.56 | 0.86 | 0.87 | 0.63 | 0.58 |
| baseline87p5 | 0.51 | 0.40 | 0.82 | 1.19 | 0.51 | 1.19 | 0.60 | 0.77 | 1.19 | 0.83 | 0.65 |
| baseline90 | | 0.41 | 0.78 | 1.63 | 0.48 | 1.63 | 0.71 | 0.70 | 3.74 | 3.74 | 0.37 |
| baseline90p3 | 0.51 | 0.36 | 0.62 | 0.86 | 0.57 | 0.86 | 0.57 | 0.86 | 0.86 | 0.62 | 0.68 |
| baseline90p5 | 0.50 | 0.53 | 1.04 | 0.91 | 0.58 | 0.91 | 0.62 | 0.79 | 0.91 | 0.74 | 0.69 |
| baseline91 | | 0.29 | 0.91 | 1.88 | 0.47 | 1.88 | 0.71 | 0.71 | 3.72 | 3.72 | 0.36 |
| baseline91p3 | 0.49 | 0.36 | 0.61 | 0.86 | 0.56 | 0.86 | 0.55 | 0.87 | 0.86 | 0.62 | 0.72 |
| baseline91p5 | 0.51 | 0.55 | 1.00 | 0.94 | 0.65 | 0.94 | 0.60 | 0.80 | 0.94 | 0.77 | 0.70 |
| baseline92 | | 0.30 | 0.91 | 1.87 | 0.44 | 1.87 | 0.66 | 0.68 | 3.70 | 3.70 | 0.34 |
| baseline92p3 | 0.51 | 0.37 | 1.29 | 0.84 | 0.59 | 0.84 | 0.55 | 0.84 | 0.84 | 0.58 | 0.67 |
| baseline92p5 | 0.44 | 0.51 | 0.98 | 0.93 | 0.63 | 0.93 | 0.60 | 0.76 | 0.93 | 0.77 | 0.68 |

**Source:** Own elaboration.

**Notes:** Each specification name encodes four attributes. The prefix indicates the flattening approach: *baseline* uses baseline flattening (three lags); *expanded* applies extended flattening (four or five lags). *baseline** shares the same baseline flattening as *baseline* but is used as a prefix to easily identify the best-performing variable grouping from the pre-selection exercise. The number following the prefix (e.g., 35, 40, 52) identifies the variable grouping. Suffixes *p3* and *p5* indicate PCA retaining 3 or 5 components; *l2* denotes two autoregressive lags of GDP; the absence of these suffixes indicates no dimensionality reduction and no autoregressive lags. *human1* refers to a judgment-based specification constructed by the authors and does not follow this naming convention. See Section 3.2 for a full description of specifications.

# Appendix

## A Estimation algorithm example

This section illustrates the estimation algorithm using a simplified example with three variables $(Y_t, X_{1t}, X_{2t})$, where $Y_t$ is the target variable and $X_{1t}, X_{2t}$ are predictors. For illustration, assume that the available dataset spans two quarters of monthly observations and is organized as follows:

| $t$ | $Y$ | $X_1$ | $X_2$ |
|---|---|---|---|
| -2 | . | m | n |
| -1 | . | o | p |
| 0 | l | q | r |
| 1 | . | b | e |
| 2 | . | c | f |
| 3 | a | d | g |

The first step of the algorithm is variable selection. To reduce the dimensionality of the predictor space, we apply Least Angle Regression (LARS). This method is not able to deal with mixed frequencies. Because the target variable is quarterly economic growth and predictors are monthly, the predictors are first aggregated to quarterly frequency. For example:

| $t$ | $Y$ | $X_1$ | $X_2$ |
|---|---|---|---|
| Q1 | l | $\bar{X}_{1Q1}$ | $\bar{X}_{2Q1}$ |
| Q2 | a | $\bar{X}_{1Q2}$ | $\bar{X}_{2Q2}$ |

where $\bar{X}_{iQj}$ is the quarter average for variable $i$ at quarter $j$.

Using this quarterly data, we compute five principal components from all predictor variables and estimate an OLS model over training and test samples. This benchmark model produces a root mean squared error denoted $RMSE_{OLS}$. We then apply LARS to select the best subset of predictors.

For illustration, suppose the algorithm selects one predictor ($n = 1$), namely $X_1$. If the resulting model satisfies $RMSE_{n=1} \leq RMSE_{OLS}$, the algorithm proceeds using the selected variables. We then return to the original monthly dataset and retain only the variables chosen by LARS:

| $t$ | $Y$ | $X_1$ |
|---|---|---|
| -2 | . | m |
| -1 | . | o |
| 0 | l | q |
| 1 | . | b |
| 2 | . | c |
| 3 | a | d |

Assume that the first quarter is used as the training period and the second quarter as the test period. All information is fully observed during the first quarter, whereas observations in the second quarter are subject to publication lags.

Suppose we evaluate the model from the perspective of period $t = 2$, one month before the realization of the target variable $Y_3$ (i.e., horizon $p = -1$). In this example, we estimate a specification that includes no principal component factors, three flattening lags, and no autoregressive terms. Furthermore, assume that $X_1$ is released with a one-month publication lag. The vintage available at $t = 2$ is:

| $t$ | $Y$ | $X_1$ |
|---|---|---|
| -2 | . | m |
| -1 | . | o |
| 0 | l | q |
| 1 | . | b |
| 2 | . | . |
| 3 | . | . |

Because $X_1$ for period $t = 2$ is not yet available due to the publication lag, the dataset contains missing observations. To address this issue, we replace missing values using the historical mean of the variable:

| $t$ | $Y$ | $X_1$ |
|---|---|---|
| -2 | . | m |
| -1 | . | o |
| 0 | l | q |
| 1 | . | b |
| 2 | . | $\mu$ |
| 3 | . | $\mu$ |

Next, we apply the data flattening procedure. For each predictor, additional columns are created corresponding to earlier months within the quarter. In this example, two additional flattened lags are constructed:

| $t$ | $Y$ | $X_1$ | $X_{1f2}$ | $X_{1f3}$ |
|---|---|---|---|---|
| -2 | . | m | . | . |
| -1 | . | o | m | . |
| 0 | l | q | o | m |
| 1 | . | b | q | o |
| 2 | . | $\mu$ | b | q |
| 3 | . | $\mu$ | $\mu$ | b |

where $X_{ifk}$ is the monthly $k$ lag for variable $i$.

Finally, we retain only the last month of each quarter so that the predictors align with the quarterly realization of the target variable:

| $t$ | $Y$ | $X_1$ | $X_{1f2}$ | $X_{1f3}$ |
|---|---|---|---|---|
| 0 | l | q | o | m |
| 3 | . | $\mu$ | $\mu$ | b |

The resulting dataset contains two periods: the first quarter serves as the training sample and the second quarter as the test observation. At the evaluation date (period $t = 2$), only the first month of the second quarter has been released due to publication lags. The model is therefore estimated using the training observation and generates a nowcast $\hat{a}$ for the second quarter using the predictor vector $(\mu, \mu, b)$.

# B Estimators

This appendix provides formal specifications and technical derivations for the estimators introduced in Section 4.3. For each model, we present the underlying equations, key assumptions, and the specific implementation choices made in this paper. The models are organized following the same three-class structure as the main text: traditional econometric models (OLS, LASSO, Ridge, Elastic Net), mixed-frequency and factor-based models (BVAR, MIDAS, DFM), and machine learning approaches (Decision Tree, GBT, Random Forest, LSTM)

## B.1 Ordinary Least Squares (OLS)

OLS regression is the most common tool of econometrics, providing unbiased, efficient estimates under the Gauss-Markov assumptions (linearity, no multicollinearity, homoskedasticity, and uncorrelated errors). The model minimizes the sum of squared residuals (Wooldridge, 2010):

$$\beta = \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 \tag{1}$$

OLS is straightforward but becomes unreliable when predictors are highly correlated or when we have high-dimensional data. To overcome these limitations within our framework, we employ PCA on all preselected variables (Stock and Watson, 2002a), retaining the first three components, as in Chinn et al. (2023), to efficiently represent the data's variance and address the curse of dimensionality. We also use OLS as a starting point before introducing regularization techniques that handle more complex data structures.

## B.2 Least Absolute Shrinkage and Selection Operator (LASSO)

When variable selection is useful (high-dimensional settings), LASSO improves upon OLS by imposing an L1 penalty, which can drive some coefficients to exactly zero (Tibshirani, 1996):

$$\beta = \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{2}$$

This property is especially valuable in high-dimensional settings, where only a subset of predictors is truly influential. However, LASSO tends to arbitrarily select one variable from a group of correlated predictors, which may not align with economic theory. In our application, LASSO is useful for variable screening (offering a contrast to the preselection PCA methodology introduced in traditional OLS) reducing a large dataset to a sparse subset before feeding them into more flexible machine learning models.

## B.3 Ridge Regression

Even when all predictors are relevant, multicollinearity can inflate OLS variances. Ridge regression counters this with an L2 penalty, which effectively shrinks coefficients toward zero without dropping any variables (Hoerl and Kennard, 1970):

$$\beta = \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{3}$$

The tuning parameter $\lambda$ controls the strength of shrinkage—higher $\lambda$ increases bias but reduces variance, improving predictive performance. Unlike LASSO, Ridge retains all predictors, making it preferable when theory suggests all variables are relevant but data exhibits multicollinearity. In our study, Ridge serves as a middle ground between OLS and LASSO, particularly useful when dealing with macroeconomic datasets where many indicators may be weakly predictive but not entirely irrelevant.

## B.4 Elastic Net

Elastic Net combines the L1 penalty (LASSO) and L2 penalty (Ridge), offering a balance between variable selection and coefficient shrinkage (Zou and Hastie, 2005). Formally, the estimator solves:

$$\beta = \sum_{i=1}^{N}(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 + (1-\lambda)\sum_{j=1}^{p} |\beta_j| \tag{4}$$

This hybrid approach is particularly useful when:

- Predictors are highly correlated (where LASSO performs poorly).
- The true model is sparse but some grouped variables should be retained (e.g., multiple lags of the same variable).

In our nowcasting framework, Elastic Net helps pre-select informative variables from a high-dimensional dataset before factor extraction, ensuring robustness against multicollinearity while maintaining interpretability.

## B.5 Mixed-frequency Bayesian VAR (BVAR)

Standard VAR models are highly parameterized and prone to overfitting, which restricts their use to small systems. To overcome this limitation, we employ a Bayesian VAR (BVAR) framework, which treats parameters as random variables and uses prior distributions to introduce shrinkage, thereby enabling robust analysis of large datasets and improving forecast accuracy. This makes the framework ideally suited for nowcasting GDP, as it can incorporate a wide array of mixed-frequency indicators (Bańbura et al., 2010; Cimadomo et al., 2020). We implement it using the mixed-frequency BVAR methodology of Ankargren and Jonéus (2020), which builds upon the state-space approach of Schorfheide and Song (2015). This approach handles mixed-frequency data by treating low-frequency series (e.g., quarterly GDP) as high-frequency series (e.g., monthly) with missing values.

The state space representation starts with the latent process which is defined as a VAR(p) equation in monthly frequency:

$$X_t = \Phi_c + \Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p} + u_t, \qquad u_t \sim N(0, \Sigma) \tag{5}$$

where $X_t$ is an $n$-dimensional vector of variables and $\Phi$ the coefficients vectors.

The equation above can be rewritten in companion form to stack $x_t$ and ease computation constraints:

$$Z_t = \Psi_c + \Psi_1 Z_{t-1} + u_t, \qquad u_t \sim N(0, \Omega) \tag{6}$$

where $\Psi$ and $\Omega$ are companion matrices of $\Phi$ and $\Sigma$.

However, we are dealing with mixed frequency variables, to address this issue real observations will be noted as $y_t$. In the case of monthly series $y_{m,t} = x_{m,t}$, but for quarterly series the following approach is adopted[15]:

$$y_{q,t} = \begin{cases} \frac{1}{3}(x_{q,t} + x_{q,t-1} + x_{q,t-2}), & t \in \{\text{Mar, Jun, Sep, Dec}\} \\ \varnothing, & \text{otherwise.} \end{cases} \tag{7}$$

With a clear depiction of the relationship between observed ($y_t$) and unobserved ($x_t$) values, we can present the observation equation:

$$Y_t = M_t \Lambda_z Z_t \tag{8}$$

where $M_t$ functions as a selection matrix and $\Lambda_t$ weighting scheme matrix, following the logic outlined in equation (8).

[15] An intraquartely average aggregation approach is useful for log-levels modelling, see Schorfheide and Song (2015). When data is transformed into growth rates, triangular weighting is recommended (Mariano and Murasawa, 2003).

To manage the high parameter dimensionality inherent in the VAR system, we follow standard Bayesian practice by imposing a Minnesota prior on the coefficient matrix $\Phi$ and an Inverse-Wishart prior on the error covariance matrix $\Sigma$, as in Schorfheide and Song (2015). This conjugate Normal–Inverse-Wishart (MNIW) prior is centered on a random walk and implemented via dummy observations, which induces a priori correlations between parameters. The tightness of the prior is controlled by a vector of hyperparameters $\lambda$.

Building on this prior specification, inference proceeds by sampling from the joint posterior:

$$p(Z, \Phi, \Sigma \mid Y) \tag{9}$$

where $Z$ are the latent monthly states and $Y$ the observed data. Because this distribution has no closed-form expression, we employ a Gibbs sampler that alternates between draws from:

$$p(Z \mid \Phi, \Sigma, Y) \quad \text{and} \quad p(\Phi, \Sigma \mid Z) \tag{10}$$

Conditional on $(\Phi, \Sigma)$, the latent states follow the smoothing distribution of a linear Gaussian state-space model and are sampled with a simulation smoother (Durbin and Koopman, 2002). Given $Z$, the parameters are conditionally independent of $Y$, so the posterior of $(\Phi, \Sigma)$ can be obtained directly from the conjugate prior.

## B.6 Mixed Data Sampling (MIDAS)

MIDAS regressions (Ghysels et al., 2004, 2016) allow to ensemble mixed-frequencies by modeling low-frequency variables directly as a function of high-frequency lags, using parsimonious weighting functions (e.g., Almon or Beta polynomials) to avoid overparameterization. The basic MIDAS specification is:

$$y_t = \beta_0 = \sum_{k=1}^{K} \beta_k B(k, \theta) x_{t-k/m} + \epsilon_t \tag{11}$$

where $xt$-$k/m$ denotes the $k - th$ lag of the high-frequency predictor (e.g., monthly data with $m = 3$ for quarterly $yt$), and $B(k, \theta)$ is a kernel function governed by parameters $\lambda$. MIDAS is particularly adept at capturing lead-lag relationships (e.g., how early-month trade signals anticipate end-of-quarter GDP).

## B.7 Dynamic Factor Model (DFM)

Dynamic Factor Models are designed to extract a small number of latent common factors from a large dataset of macroeconomic indicators. These latent factors capture the underlying co-movements across variables (as those driven by business cycle dynamics) while allowing for variable-specific noise through idiosyncratic components (Stock and Watson, 2002b; Giannone et al., 2005). Each observed variable is modeled as a linear combination of these common factors plus an error term:

$$y_{i,t} = \lambda_{i,1} f_{1,t} + ... + \lambda_{i,r} f_{r,t} + \epsilon_{i,t} \tag{12}$$

where:

$y_{i,t}$ is the observed variable,

$f_{j,t}$ are the latent factors,

$\lambda_{i,j}$ are factor loadings, and

$\epsilon_{i,t}$ are idiosyncratic shocks.

To capture temporal dynamics, the model is cast in a state-space form, where the factors evolve according to a vector autoregressive (VAR) process:

State equation:

$$F_t = AF_{t-1} + u_t \tag{13}$$

Observation equation:

$$y_t = CF_t + e_t \tag{14}$$

This formulation enables recursive real-time updating via the Kalman filter, which is especially useful in nowcasting environments characterized by ragged-edge, mixed-frequency, and incomplete data. Estimation follows the two-step procedure outlined in Bok et al. (2018): initial factor estimates are obtained via principal components, and model parameters are refined using the Expectation-Maximization (EM) algorithm, which iteratively applies the Kalman filter and smoother to estimate the latent states (E-step), and then updates parameters to maximize the expected likelihood (M-step).

## B.8 Decision Tree Regression

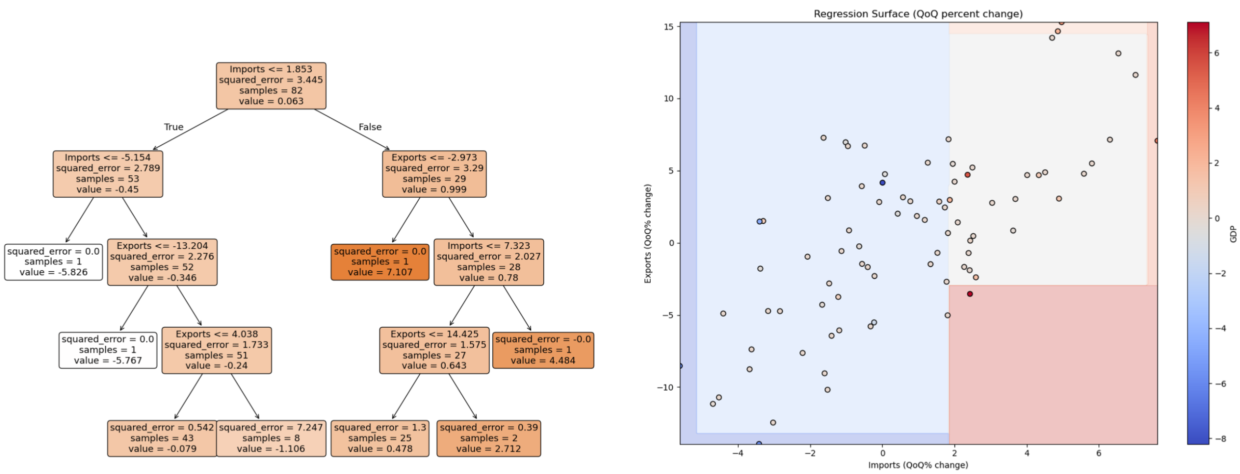
As we transition from traditional econometric models to machine learning, decision tree regression offers a fundamental yet powerful nonlinear approach for modeling relationships in high-dimensional data. Unlike linear models constrained by Gauss-Markov assumptions, decision trees recursively partition the feature space into nodes using binary splits.

Each split is determined by a threshold on an explanatory variable, chosen to minimize the variance of the target variable within the resulting subsets. This recursive partitioning continues, creating internal nodes until a stopping criterion is met (e.g., maximum depth or minimum node size), ultimately yielding leaf nodes where predictions are made based on the average target value of observations in that region.

The most widely used algorithm for this purpose is CART (Classification and Regression Trees; Breiman et al., 1984), which examines all predictors and employs a greedy approach to minimize the mean squared error at each node. This process is shown in Figure B1a, with a regression tree for GDP prediction where each node displays the splitting variable and threshold, the resulting improvement in model fit, and the number of observations, with the final predictions shown in the terminal leaves.

Because CART is a top-down procedure that does not revise earlier splits in light of later ones, predictions at each terminal leaf are simply the mean GDP growth of all training observations routed to that region. Figure B1b makes this structure visible through a deliberately simplified two-feature example (using only QoQ% changes in imports and exports) so that the full decision surface can be plotted in two dimensions; in practice, the model draws on the complete set of predictors described in Section 3. Each rectangular region corresponds to one terminal leaf and predictions are uniform within each region, changing only at the boundaries defined by the splitting thresholds. Note that distinct leaves may share similar colors when separately partitioned regions yield comparable mean GDP growth rates, a visual coincidence that does not imply model equivalence.

Figure B1: Decision Tree Regression example




(a) Regression tree

(b) Regression surface (QoQ%)

**Source:** Own elaboration.

**Notes:** Figure B1 presents a Decision Tree Regression model trained to predict quarterly real GDP growth (QoQ%) using QoQ% changes in imports and exports from The Bahamas' main trading partners as the only two features, deliberately simplified to allow visualization of the full decision surface. Panel (a) shows the full tree structure: each internal node reports the splitting variable and threshold (True = left branch, False = right branch), the resulting MSE, and the number of observations routed through it; terminal leaves report the predicted GDP growth value. Panel (b) shows the corresponding two-dimensional regression surface, with QoQ% import growth on the horizontal axis and QoQ% export growth on the vertical axis, colored by predicted GDP growth value. Scatter points represent actual training observations colored by their realized GDP growth.

## B.9 Gradient Boosted Regression Trees (GBT)

Gradient boosting addresses the weaknesses of single trees by iteratively combining weak learners (shallow decision trees) to correct residual errors. The model takes up on an optimization problem, instead of fitting the tree to residuals, it fits to the negative gradient of the loss function with respect to the latest model's predictions Friedman (2001). This gradient represents the direction and magnitude of change needed to reduce the loss. In this paper we use squared error as the loss function: $L(y, F(x)) = (y - F(x))^2$, meaning that the gradient is $-(y - F(x))$, or the residual. At each iteration the model updates the prediction:

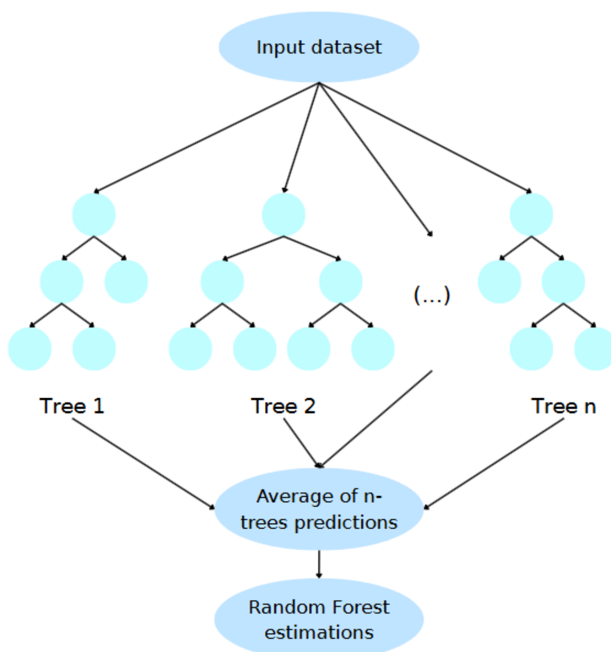
$$F_m(X) = F_{m-1}(X) + \upsilon * h_m(X) \tag{15}$$

where $\upsilon$ is the learning rate (shrinkage parameter) controlling step size. GBT's sequential learning allows it to adaptively focus on hard-to-predict observations, making it ideal for nowcasting tasks with noisy, high-frequency data. In our framework, GBT serves as an improvement to decision trees, evaluating whether boosting's progressive refinement outperforms simpler tree-based or linear models.

### B.10 Random Forest Regressor

While gradient boosting builds trees sequentially, random forests (RF) train an ensemble of trees in parallel (as shown in figure B2) averaging their predictions to reduce variance (Breiman, 2001). Each tree is grown on a bootstrapped sample of the data, and at each split, only a random subset of predictors is considered. This use of randomization reduces correlation between trees, improving generalization.

Figure B2: Random Forest Regression diagram




**Source:** Own elaboration, based in Sahour et al. (2021)

**Notes:** The top figure illustrates the architecture of the Random Forest Regression algorithm. The diagram shows how the model builds an ensemble of decision trees, each trained on a random subset of the data and features. The final prediction is obtained by averaging the outputs of all individual trees.

RFs are robust to outliers and irrelevant predictors, making them suitable for high volume datasets. However, RFs may underperform in pure time-series settings due to their disregard for temporal dependencies, a gap addressed by recurrent neural networks like LSTMs.

## B.11 Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM; Hochreiter and Schmidhuber, 1997) is a variation of recurrent neural network (RNN) architecture designed to address the vanishing and exploding gradient problems present in traditional RNNs, particularly when learning long-term dependencies. The LSTM maintains two key states: the cell state ($C_t$) serves as the network's long-term memory, preserving information across many time steps with minimal changes, and the hidden state ($h_t$) which functions as its immediate context representation, containing processed information for current predictions. As reviewed by Van Houdt et al. (2020), a LSTM unit consists of a memory cell and three gating mechanisms:

Input gate:

$$i_t = \sigma(W_i x_t + R_i h_{t-1} + p_i c_{t-1} + b_i) \tag{16}$$

Forget gate:

$$f_t = \sigma(W_f x_t + R_f h_{t-1} + p_f c_{t-1} + b_f) \tag{17}$$

Output gate:

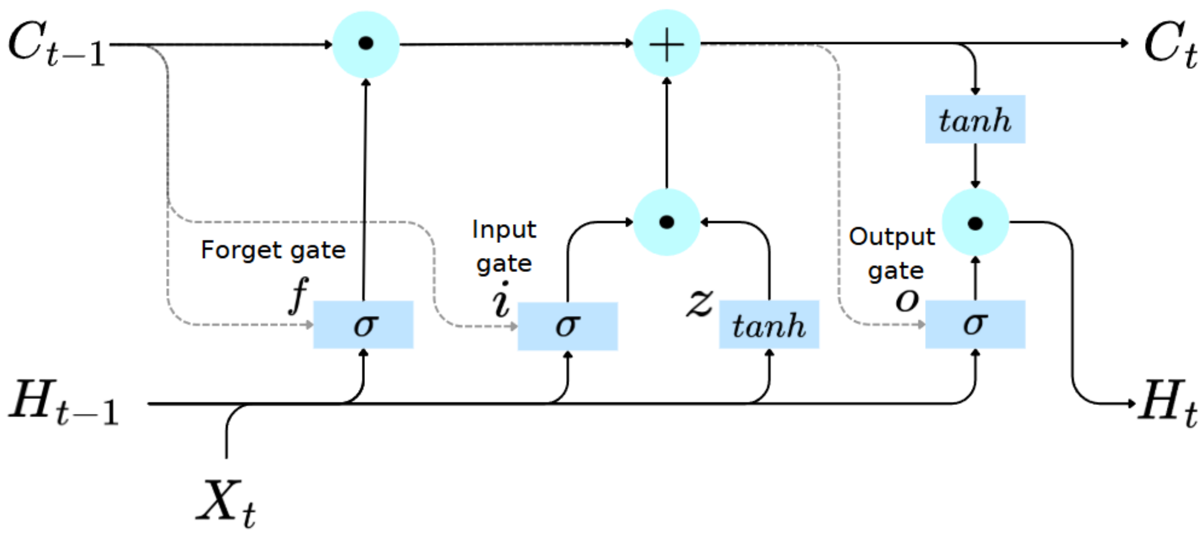
$$o_t = \sigma(W_o x_t + R_o h_{t-1} + p_o c_t + b_o) \tag{18}$$

Additionally, a block input is later conjugated with the input gate:

$$z_t = tanh(W_z x_t + R_z h_{t-1} + b_z) \tag{19}$$

The weight matrices $W*$ (input weights), $R*$ (recurrent weights), and $p*$ (peephole weights) are learned during training, governing how input features, hidden states, and cell states influence each gate. The biases $b*$ provide additional flexibility. $X_t$ is the vector of features, $C_{t-1}$ is the previous cell state, $C_t$ is the current cell state, $H_{t-1}$ is the previous hidden state and and $H_t$ is the current hidden state.

Figure B3: LSTM cell architecture




**Source:** Own elaboration, based in Van Houdt et al. (2020)

**Notes:** This figure illustrates the architecture of a single Long Short-Term Memory (LSTM) cell. The diagram shows the cell state (C) and hidden state (H) flowing through time, regulated by the input, forget, and output gates (using sigmoid activation, $\sigma$) and candidate value updates (using tanh activation). Peephole connections are indicated by dotted lines.

As seen in figure B3, the gates regulate information flow into and out of the cell state, each using sigmoid activation ($\sigma$) to produce values between 0 and 1. These gating values determine what information to retain or discard at each step. Meanwhile, the hyperbolic tangent (*tanh*) activation transforms candidate updates, normalizing them to (-1, 1) for stable cell state modifications. Together, sigmoid gates control how much information flows while *tanh* determines how that information is represented in memory. This architecture is enhanced by peephole connections (dotted lines) that allow gates to inspect the cell state directly, enabling precise control over information retention and propagation while maintaining gradient stability during training. The cell state undergoes an additive update which combines filtered historical information with gated new inputs:

$$c_t = z_t \odot i_t + c_{t-1} \odot f_t \tag{20}$$

where $c_t$ is the updated cell state at time $t$, $z_t$ is the block input (candidate update), $i_t$ is the input gate activation controlling how much of the candidate update to write into memory, $c_{t-1}$ is the previous cell state, $f_t$ is the forget gate activation controlling how much of the previous cell state to retain, and $\odot$ denotes element-wise multiplication.

In the final step, the hidden state is computed below representing the LSTM's output for the current time step.

$$h_t = tanh(c_t) \odot o_t \tag{21}$$

# C Glossary of machine learning terms

Table C1: Key machine learning concepts and their sources

| **Concept** |
|---|
| **I. General concepts** |
| **Ensemble methods.** Learning algorithms that construct a set of estimators and combine their predictions—via a w average or majority vote—to produce a final output. No single model reliably approximates the true data-generating pooling diverse models reduces variance and guards against overfitting. In this paper, ensemble methods refer to co predictions from hundreds of model-specification-estimator combinations, weighted by their inverse RMSE. |
| **Overfitting.** A condition in which a model fits the training data too closely—capturing noise rather than the underlying sign consequently fails to generalize to out-of-sample observations. More likely when parameters greatly outnumber observation nosed by a large gap between in-sample and out-of-sample performance. Regularization, cross-validation, and ensemble av are standard remedies. |
| **Regularization.** A family of techniques constraining model complexity by adding a penalty to the objective function, disco parameters from becoming too large. While economists are familiar with penalized regression (ridge, LASSO), the ML lit uses 'regularization' more broadly to encompass any mechanism—including dropout, weight decay, and early stopping purpose is to reduce overfitting and improve out-of-sample generalization. |
| **Hyperparameter.** A configuration value governing a learning algorithm that is not estimated from the training data. Se training begins (e.g., $\lambda$ in LASSO, number of trees in a Random Forest, learning rate in gradient boosting), and typically t a held-out validation set—in contrast to model parameters such as regression coefficients, which are estimated from the da |
| **Bootstrap sampling.** A resampling procedure in which repeated samples of size $n$ are drawn with replacement from the training dataset. Each bootstrap sample trains a separate model (e.g., a decision tree in a Random Forest), and the d introduced reduces correlation between models, lowering overall prediction variance. Distinct from the parametric boots econometrics, which serves primarily as an inference tool. |

**Table C1**

| Concept |
|---|
| **Greedy algorithm.** An optimization approach making locally optimal choices at each step without reconsidering prior decis decision tree construction (CART), the greedy approach selects the best variable and threshold at each node—the split ma reducing prediction variance—without evaluating all possible future splits. Computationally feasible, but does not guar globally optimal structure. |
| **Learning rate.** A hyperparameter—sometimes called the shrinkage parameter—controlling the step size at each iteratio optimization algorithm. In gradient boosting, the learning rate $\nu$ scales each new tree's contribution: a smaller value requir trees but typically improves out-of-sample performance. In neural network training, it governs the magnitude of weight upo each gradient descent step. |
| **Factor-based approach.** A dimensionality reduction strategy summarizing a large number of observed variables into number of unobserved latent factors assumed to drive their common variation. Reduces the effective number of predictors fe estimator while preserving the informational content of the full variable set. In this paper, Principal Component Analysis extracts factors prior to estimation. |
| **II. State-space models** |
| **Latent state (State-space model).** A state-space model represents a time series as two equations: a state equation gover evolution of an unobserved (latent) vector, and an observation equation linking that vector to the data. The latent state c the underlying dynamic process (e.g., a monthly GDP path inferred from quarterly observations), while the observation e accommodates measurement error and mixed-frequency data. The Kalman filter provides the standard recursive algori computing the expected latent state given information up to time $t$. |
| **Smoothing.** Computing the conditional distribution of the latent state at time $t$ given the full observed sample—includin observations—rather than only information up to $t$ (filtering). Smoothed estimates are more precise than filtered estimates the standard output used in parameter estimation via the EM algorithm. Not to be confused with nonparametric curve sm (e.g., moving averages). |
| **Simulation smoother.** A procedure that draws random samples from the conditional distribution of the latent stat the full observed sample and model parameters. Unlike the mean smoother, which returns only the expected state, the sim smoother produces entire trajectories of the latent process, enabling Bayesian inference via Gibbs sampling and likelihood eva via importance sampling. Computationally efficient because it exploits Kalman filter recursions rather than constructing joint covariance matrix. |
| **III. Long Short-Term Memory (LSTM) networks** |
| **Recurrent Neural Network (RNN).** A class of neural networks built for sequential data. Unlike a feedforward netw RNN maintains a hidden state $h_t$ updated at every time step as a function of the current input $x_t$ and the previous hidd $h_{t-1}$, providing a form of memory without expanding the parameter count as the sequence grows. Standard RNNs enco fundamental training problem on long sequences—the vanishing and exploding gradient—that severely limits their ability t distant information. The LSTM was developed as a direct architectural response to this failure. |

**Table C1**

| Concept |
|---|
| **Vanishing / exploding gradient.** The central training difficulty of standard RNNs. During backpropagation, gradien backwards through every time step via repeated multiplication of a partial-derivative matrix. When that matrix has a do singular value below one, the product shrinks exponentially toward zero (vanishing), so early time steps receive almost no l signal. When it exceeds one, the product grows without bound (exploding), causing numerically unstable updates. The resolves the vanishing case by routing long-run information through an additively updated memory register that bypasses re matrix multiplications. |
| **Activation function.** A nonlinear function applied to the weighted inputs of a network unit. Without activation fun any composition of linear transformations remains linear, making the network no more expressive than a single linear reg regardless of its depth. Two activation functions appear in the LSTM: the sigmoid $\sigma(\cdot)$, used in the three gate equations to p values in $(0, 1)$ acting as continuous open/close controls, and the hyperbolic tangent $\tanh(\cdot)$, used to transform candidate m content and normalize the cell state before output. |
| **Sigmoid function** [$\sigma$]**.** Defined as $\sigma(x) = 1/(1 + e^{-x})$. Maps any real input to the open interval $(0, 1)$, producing a bo smooth S-shaped curve. In the LSTM, $\sigma(\cdot)$ appears in all three gate equations ($i_t$, $f_t$, $o_t$), where its output determines how of a given memory signal is passed through at each step. The sigmoid saturates at the extremes of its domain, though in roles this produces desirable clean open/close decisions. |
| **Hyperbolic tangent** [tanh]**.** Defined as $\tanh(x) = (e^x - e^{-x})/(e^x + e^{-x})$. Maps any real input to $(-1, 1)$. Unlike the s tanh is zero-centered—outputs symmetric around zero—producing better-behaved gradients during training. In the LSTM bounds the candidate values written into the cell state (block input $z_t$) and normalizes the cell state in the computation hidden state $h_t$. Where sigmoid controls flow, tanh shapes content. |
| **Weight matrices and bias vectors** [$W_*$, $R_*$, $p_*$, $b_*$]**.** The learnable parameters of the LSTM, all estimated via backpropa Input weight matrices $W_i$, $W_f$, $W_o$, $W_z$ scale the current input $x_t$. Recurrent weight matrices $R_i$, $R_f$, $R_o$, $R_z$ scale the p hidden state $h_{t-1}$. Peephole weight vectors $p_i$, $p_f$, $p_o$ scale the cell state directly. Bias vectors $b_i$, $b_f$, $b_o$, $b_z$ are structurally d added unconditionally without scaling any input, they set the baseline activation of each gate when all inputs are zero—an to the intercept in a linear regression. A large positive forget-gate bias encodes a prior toward retaining memory; a large n input-gate bias toward not writing new content. |
| **Peephole connections** [$p_i$, $p_f$, $p_o$]**.** An extension to the standard LSTM in which each gate conditions directly on the ce in addition to the input and hidden state. Without peepholes, gates observe only the filtered view of memory exposed t $h_{t-1}$. Peephole connections give the forget and input gates direct access to $c_{t-1}$, and the output gate to $c_t$, enabling more timing and counting patterns. The paper presents the peephole-augmented form as the default specification. |

**Source:** Own elaboration based on cited references.